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Deep Learning Topology for Islanding Detection for Distributed Generation (Sags-Swells)

A Thesis Submitted in Partial Fulfillment of the Requirements for the
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Abstract

Distributed generation (DG) presents a viable strategy to meet the rising demand for energy by producing power at the point of consumption through conventional energy or renewable sources. The integration of DGs into microgrids leads to improved power supply reliability for end users. These microgrids can function in either a grid connected or in an autonomous islanded mode. Identifying islanding events in which a DG segment becomes electrically isolated from the main grid is critical for safely linking a DG with the larger utility network. From an engineering management perspective, implementing reliable islanding detection systems requires careful consideration of technology selection, system integration, and maintenance protocols. Additionally, effective coordination among engineering teams, regulatory bodies, and utility operators is essential to establish clear standards, ensure compliance, and optimize system performance.

By addressing these management considerations, the seamless integration of DG into the utility network can be achieved while prioritizing safety, reliability, and operational efficiency. Numerous strategies for detecting islanding have been introduced to enhance the detection speed and precision. However, these methods require an infusion of intelligent capabilities to ensure accuracy during low power discrepancies and in the presence of electrical noise. This research is introducing the use of Artificial Intelligence based approaches and algorithms for islanding detection. It involves transforming electrical data from the point of common coupling into images and time series signals. A comprehensive dataset representing various islanding and non-islanding scenarios has been compiled through dynamic system for the development and validation of machine learning and deep learning algorithms.

The study uses Convolutional Neural Network (CNN) topology for islanding detection techniques. The innovation is the early islanding detection feature which monitors for faults and normal operations, exploiting the brief interval between relay activation and

circuit breaker disengagement to identify islanding occurrences. The proposed model has been validated using a special dataset made for islanding that has cases where the power is noisy, and the data is messy. The study used 1000 trends across various parameter protections to train, validate, and test the model. Overall accuracy rates were mostly above 94%, highlighting the potential of these models as reliable tools for islanding detection across various protections, demonstrating the high effectiveness of these methods in islanding detection.

Publications and Participations

- i.* Abdulraouf Almubarak and Ebrahim Mattar, " Implementation of Islanding Protection System into SIMULINK Model," the 7th Smart Cities Symposium (SCS 2023), page 667-671 doi: 10.1049/icp.2024.1036, IET Inspec indexed. ISBN: 978-1-83953-993-0, Location: Conference, Bahrain, Conference date: 3-5 December 2023, Publisher: IET.
- ii.* Abdulraouf Almubarak and Ebrahim Mattar, "Islanding Detection Classification Using Artificial Neural Networks," the 7th Smart Cities Symposium (SCS 2023), page 662-666 doi: 10.1049/icp.2024.1035, IET Inspec indexed. ISBN: 978-1-83953-993-0, Location: Conference, Bahrain, Conference date: 3-5 December 2023, Publisher: IET.
- iii.* Islanding Detection Classification Using Convolutional Neural Network (CNN).
(Submitted for journal publication).
- iv.* Exploring Deep Learning Topology for Islanding Detection for Distributed Generation.
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Dedication

To my parents, family and friends

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Abbreviations

DG – Distributed Generation
PQ – Power Quality
CNN – Convolutional Neural Network
DNN – Deep Neural Network
ANN – Artificial Neural Network
SVM – Support Vector Machine
NDZ – No Detection Zone
PCC – Point of Common Coupling
AC - Alternating Current
DC - Direct Current
IDMs – Islanding Detection Methods
AFD – Active Frequency Drift
SFS – Sandia Frequency Shift
SVS – Sandia Voltage Shift
SFS – Slip Mode Frequency Shift
UOV – Under/Over Voltage
UOF – Under/Over Frequency
MATLAB - Matrix Laboratory
SDFT - Sliding Window Discrete Fourier Transform
EMD - Empirical Mode Decomposition
PJD – Phase Jump Detection
RoCoP – Rate of Change of Power
RoCoF – Rate of Change of Frequency
PLCC – Power Line Carrier Communication
SCADA – Supervisory Control and Data Acquisition
WT – Wavelet Transform

TTT - Time-Time Transform
ST – S-Transform
FT – Fourier Transform
STFT – Short Time Fourier Transform
FFT – Fast Fourier
AI – Artificial Intelligence
FL – Fuzzy Logic
RMS – Root Mean Square
RBF – Radial Basis Function
MLA - Machine Learning Algorithms
PNN – Probabilistic Neural Network
THD – Total Harmonic Distortion
BFVB – Basic Frequency Variable Bridge
PT- potential transformer
CT- Current transformer
DT- Decision tree
NB - Naive Bayes
RFC - Random Forest Classifier
MBM - Multiplier-based method
ST - S-Transform
RPNN - Ridgelet Probabilistic Neural Network
APBM - Andrews plot-based method
MG - Microgrid
THD - Total Harmonic Distortion
DLL - Dynamic-link library
ROC - Receiver Operating Characteristics
DFIG - Doubly-Fed Induction Generators
PV- Photovoltaics
PLCC - Power Line Carrier Communication
IGBT – Insulated Gate Bipolar Transistor

PWM – Pulse Width Modulation

SVPWM – Space Vector Pulse Width Modulation

CWT – Continuous Wavelet Transform

PSEC/ FD – Power System Event Classification / Fault Detection

2D Two-Dimensional

3D Three-Dimensional

Chapter 1

Introduction

Chapter 1 Introduction

1.1 General

With increasing in load demand for future electricity grids, it is important to consider an integration of distributed generation, where this paradigm is expected to play an increasingly important role. In most power systems, power flows from a number of scattered generating power plants to consumers via power networks (i.e., transmission and distribution networks). In case of the appearance of any disturbance or any abnormality in these power networks, it will be required to isolate some of the generating power plants and to allow them to operate separately from the main transmission network. This requires finding a method for islanding detection system to determine the situations in which the power plant must be separated from the transmission lines and avoid tripping the units by their respected protection relays. Therefore, an accurate and fast islanding detection technique is needed to overcome these issues. Islanding detection techniques are dependent on network fault and connection type of the distributed generation to the network system. A major challenge is to design an (islanding model technique) to detect islanding very accurately and in an optimized time consumption manner for different distributed generation scheme types and for multiple units connecting together in power network-grid.

Recent studies and research directions indicate that (AI) Artificial Intelligence techniques and new methods have been applied to a large number of applications related to power systems. This includes a wide spectrum from generation stage, directly into an end side (the user and consumers) of the power grid. Definitely, there are a number of advantages behind this move towards (AI) related power managed and protected systems. Of particular

importance of this move, is the availability of updated and quick access to dataset (big data) from the different resources of the wide power systems. There are a number of approaches related to using Artificial Intelligence for the domain of power systems deliveries. Examples of which are the approach adopted by Liu et. al. [1] where they stated that “Data-driven methods designed for acquiring hidden knowledge from empirical data gradually attract the researchers” interest, where Machine Learning Algorithms (MLA) provide a promising way to meet such challenges brought by big data, as Liu et. al. [1].

Of particular importance, as in Styvaktakis et. al. [2], the study proposed an algorithm or an expert system that classifies and analyzes different voltage events in power system by using sensing voltage waveform behavior. The algorithm was built to classify the voltage events or faults for both over and under voltage situations. The developed algorithm considers the voltage as abnormal if it is not within (*1.05 and 0.95 pu range or band*) and that can be classified by analyzing the voltage waveforms to fault like interruption, single/multi stages faults or to normal events like energizing, transformer saturation or step change operation etc... The voltage magnitude or level, the frequency fluctuations and harmonics order and level are the main factors that have been used in the model. The model analyzes different stages of voltage events and that is by using Kalman filters to identify frequency magnitude and the harmonics of the voltage waveforms. The (AI) classification model is used to check the number of event segments and result with the event or fault classifications according to certain specific expert rules. The rules lead to identify the events to either (fault events) or (normal operation events). In addition, an expert system had been applied in the actual medium voltage

network and the result was (97%) of the events were classified correctly by the system. There were some events not classified because either there was no stage in voltage dips or no step change in the voltage waveforms of those events. In addition, when testing the model and as far as the protection operation of concern, transformer saturation and fuse blowing could not be detected by the proposed model. But overall, the developed expert system is a very useful technique to analyze and classify the recorded power system events which can be used in supervision and control in any power system. In a contrary contrast, in [3], Krishnan and Gaonkar have justified the rapidly increasing demand for electricity, clubbed with the need for environment friendly resources, is accelerating the entry of more and more distributed generation into the power system network.

In [5], Mollah, for the purpose to meet the increasing load demand of future electricity grids, in addition, in the proposed method, features are extracted from five network variables associated with voltage signal. In this respect, a support vector machines (SVM) based Method for islanding detection was proposed. The extracted features are then used as inputs to the support vector machines (SVM) based approach and which end up with classifying the event as islanding or non-islanding with a special emphasis on the most critical islanding cases associated with NDZ of VS and ROCOF relays (indicate the full words of the NDZ and ROCOF terms). In [6], Fadzil et. al., IDMs can be broadly classified as classical method or modern method. Classical methods include local methods and communication-based or remote method, while modern method includes SP-based, method and Artificial Intelligence (AI) method.

1.2 Research Problem

Given the previous background, this thesis proposal is related to aiming at presenting another or alternate innovative approach for detection, classification and characterization of abnormalities of events that might occur in electricity networks. There are a number of causes related to disturbances in electricity networks where faults in electricity networks, and abnormal events are created. In particular, one of such abnormal disturbances event is the formation of power system islanding containing the distributed generating resources, where the other is the voltage dips, sags and or swells. The thesis is related to the use of more recent (Deep Learning) Machine Learning tools-based approach, in particular machine learning classification and decision-based systems, for the detection and classification of islanding events in a distribution network embedded with Distributed Generation. In addition, for the purpose of detecting, classifying and the characterization of voltage dips or swells in electricity networks, the thesis will also look into other two new methodologies. The machine learning tools will be tested with more special emphasis on the most critical happening related to islanding cases associated with NDZ of VS and ROCOF relays. In addition, there are a number of possible combinations of deficit and excess of active and reactive power imbalance, which may exist during an occurrence of an island, to be considered during the testing phase. It is very important after detecting such an islanding condition to quick control to prevent its severe consequences from their occurrence. Thus, Islanding detection technique can be analyzed and classified according to the type of fault for intelligent automatic switching system.

1.3 Research Objectives

- To design a dynamic model using simulation software to replicate electrical protection mechanisms for islanding detection, as well as to generate datasets for various grid disturbance scenarios.
- To develop logarithm for classification of such large amount of system dataset and analyzing the islanding events.
- To design an intelligent islanding based on Deep Learning detection system using Convolution Neural Networks Techniques that can handle all possible combinations of power imbalance scenarios and at the presence of different types of generation schemes which integrated with automatic switching system for islanding operation.
- Integrating these technical advancements with efficient engineering management practices to ensure seamless implementation, monitoring, and optimization of the islanding system.

1.4 Research Questions

- How can a deep learning system using CNN techniques be designed to handle all possible combinations of power imbalance scenarios and various generation schemes in islanding detection?
- What challenges and strategies are involved in developing an algorithm capable of classifying and analyzing a large amount of data for islanding event detection?
- How can AI be integrated into an automatic switching system to enhance islanding operation, and what are the key factors in its design and implementation?

- How does the CNN-based deep learning system adapt to different types of generation schemes, and what are its implications for system robustness and reliability?
- How does the system characterize various network disturbances, and how does this characterization influence the automated switching response in islanding operations?
- In what ways does the proposed AI and deep learning-based approach advance over traditional islanding detection methods in terms of accuracy, response time, and adaptability?

1.5 Research Significance

- The use of CNN and deep learning techniques represents a significant advancement in the field of islanding detection. Traditional methods may not effectively handle complex scenarios with diverse power generation schemes and imbalances. The proposed system can potentially offer greater accuracy and efficiency.
- The ability to handle all possible combinations of power imbalance scenarios and different types of generation schemes is crucial for modern power grids, which are increasingly complex and variable due to the integration of renewable energy sources.
- Developing an algorithm capable of classifying and analyzing large amounts of system data is significant for the broader field of power system analytics. This capability is essential for managing and optimizing increasingly data history power systems.

- Building an AI-based automatic switching system represents a pioneering step in integrating artificial intelligence into power grid operations. This integration can lead to more autonomous, efficient, and resilient power systems.
- The ability to classify and characterize network disturbances and subsequently respond with appropriate switching actions can greatly improve the adaptive capacity of the power grid, ensuring stability under varying conditions.
- The methods being developed in this research can be used in these future smart power grids, making them better at handling new situations and needs. This is really helpful for making sure our electricity systems stay strong and flexible as they grow and change.

1.6 Research Outline

The thesis comprises seven chapters. CHAPTER 1 outlines the introduction to the study. CHAPTER 2 discusses the theoretical framework and provides the literature review of islanding detection. CHAPTER 3 and 4 describe the model used in the simulation software and simulates the electrical protection for islanding detection in addition to generating dataset. CHAPTERS 5 explains the intelligent islanding based on Convolution Neural Networks Techniques and describes the algorithm classification model and validate the model by using number of real datasets to build an (AI) based automatic switching system for islanding operation. Results and discussions are illustrated in CHAPTER 6. Finally, CHAPTER 7 provides the conclusions followed by some ideas on future work.

1.7 Summary

The research objectives outlined a comprehensive plan to design an intelligent islanding detection system using Convolutional Neural Network (CNN) techniques, capable of handling various power imbalance scenarios and generation schemes. Additionally, the development of algorithms for classifying and analyzing large datasets related to islanding events was targeted, along with the creation of an AI-based automatic switching system to enhance islanding operation. These technical advancements were to be integrated with efficient engineering management practices to ensure seamless implementation, monitoring, and optimization of the islanding system. Several research questions were posed to guide the investigation, focusing on the design and implementation challenges of the proposed system, as well as its adaptability to different generation schemes and network disturbances. The significance of the research lies in its potential to advance islanding detection beyond traditional methods, offering greater accuracy and efficiency, especially in complex and variable power grids with diverse generation sources. Moreover, the integration of AI into power grid operations could lead to more autonomous and resilient systems, capable of responding effectively to network disturbances. The research outline delineated the structure of the thesis, spanning seven chapters. These chapters include an introduction to the study, a theoretical framework and literature review, discussion and simulation of electrical protection for islanding detection, implementation of CNN-based intelligent islanding detection, validation of classification algorithms, and results analysis. The thesis concludes with a summary of findings and suggestions for future research directions.

Chapter 2

Literature Review

Chapter 2 Literature Review

2.1 Introduction

Presently days, nearly all power utilities require that the distributed generation ought to be disconnected from the network when there is a conceivable case of islanding without taking any chances. This is as per (IEEE standard) that requires the detachment of DG when it is islanded. Actually talking, control quality can be undermined when islanding happens and can cause unstable to voltage and frequency, which cannot be kept up within standard reasonable level. The base or the reasoning of islanding detection is to screen and watch the parameters of the generator at that point common with transmission and comparing it with the protection setting that tripped the generator.

2.2 Islanding Detection Classification

There are several islanding detection methods, which can be categorized into three main techniques: remote, local and machine learning techniques as shown in Figure 2.1. The remote islanding detection concentrates on the abnormality operation of the transmission and load utilities which sense the fault or abnormal operation and send the command to activate the islanding mode through communication channel. It is a very reliable and fast method but normally expensive and complicated. However, the remote islanding detections depend on the measurement of PT and CT at generation side. The deviation of the frequency and voltage between generator side and utilities side may consider small different which called active detection or called passive detection if large difference in the larger average values. Machine learning techniques is one of the most important islanding detections in recent

decades, which do not require any communication medium as used in remote techniques, and also no threshold settings as in local techniques. Machine learning techniques depend on signal processing techniques that are computationally complex of artificial neural networks (ANNs), support vector machines (SVMs) and decision tree (DT) .It is very fast detection, and high accuracy.

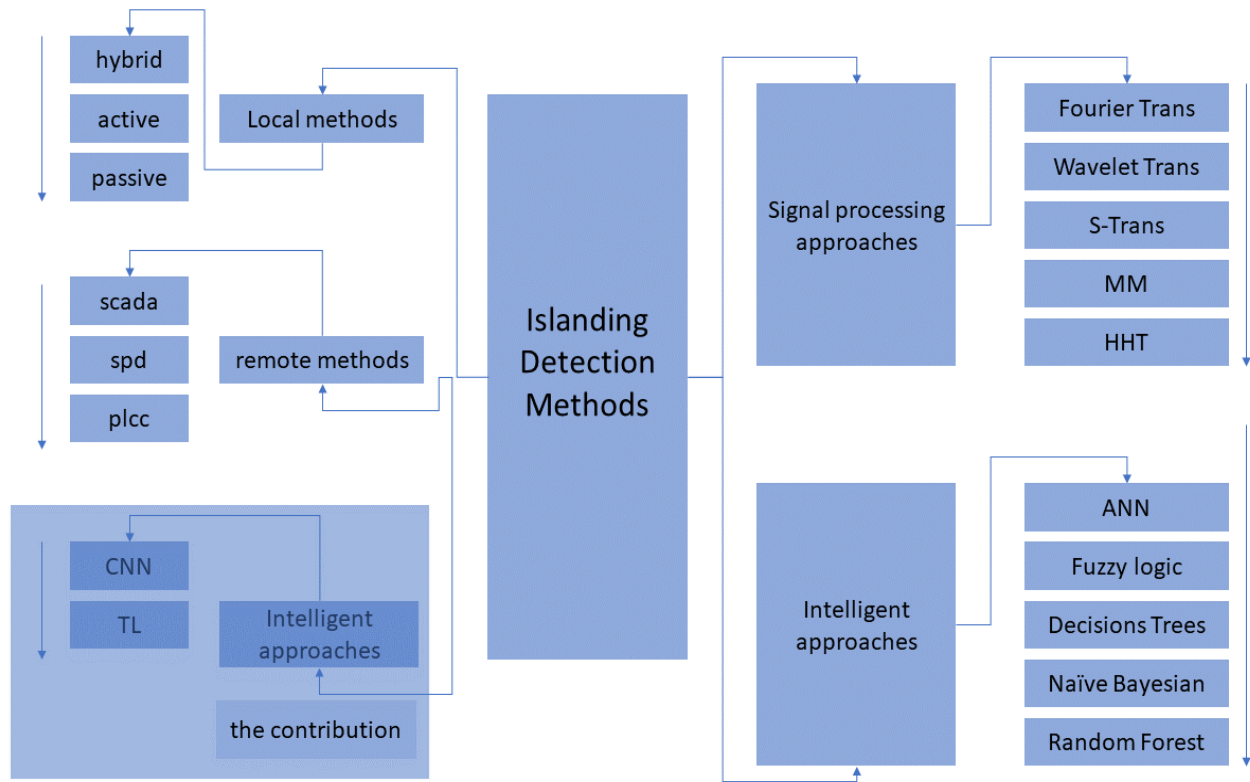


Figure 3.1 Typical Islanding Detection methods.

2.2.1 Remote Islanding Detection Techniques

Remote islanding detection methods are use the communication channels like fiber optic, power line communications, GPS between generation units and utilities in transmission and distribution to transmit islanding and non-islanding signals. It is a very useful method especially for large networks

which monitor all the untidies in the network in different locations of the generation plants and different distribution feeders. It is considered as excellent reliable option and a small non-detection zone although it is considered expensive and therefore not economical.

The main remote islanding detection techniques are as follows:

1. *Transfer Trip Scheme*: A transfer trip logic can be characterized as the way of checking particular circuit breakers and re-closers in transmission lines or distribution systems for the reason of island detection. To screen this, the transfer trip logic integrated with supervisory control and information acquisition. This strategy needs great and strong communication between the utility and the DGs.
2. *Power Line Carrier Communication Scheme (PLCC)*: PLCC is in charge of broadcasting a flag within the transmission network to the distribution feeders utilizing the control line as a carrier media. In each DG, there's a collector that gets signals. Once it does not distinguish a flag, the switch from network associated to islanded mode happens. The control logic is viewed as a successful discovery strategy within the case of different DGs.

2.2.2 Local Passive Islanding Detection Techniques

Local detection strategies that are fundamentally based on the measurement through the CT and PT parameters like voltage, frequency on the generation side. This detection can be passive or active detection.

The fundamental of the Passive methods is monitoring the electrical quantities of the network system at the point of common coupling with transmission lines as shown in block diagram at Figure 2.2. The islanding occurs when changes in these quantities like Under/over voltage/frequency, rate of change

of frequency (ROCOF) reached to above certain protection limits are detected. The voltage and the frequency changes may not be sufficient to detect the islanding if the loads in the island region are close to generation and that will be leading to large non-detection zones.

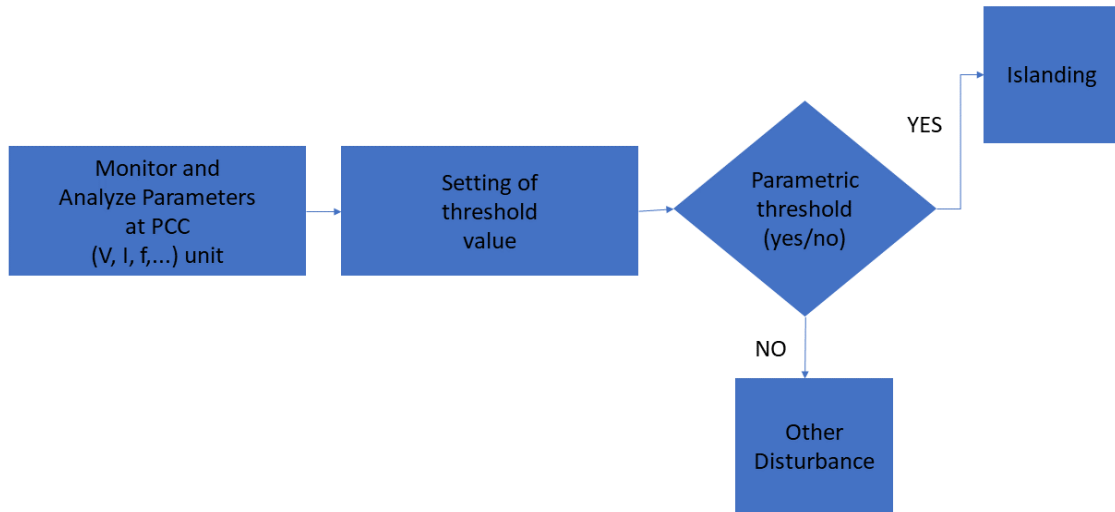


Figure 3.2 Block diagram of passive islanding detection methods.

Passive strategies are based on the data accessible on the DG location at the point of common coupling (PCC) with the network. However, the effectiveness of passive strategies isn't ensured for the situation that the load and the generation are balanced. The passive detection method normally does not require additional equipment and can be implemented at low cost. The main passive islanding detection techniques are introduced below as follows:

1. *Under/Over Frequency*: Normally, Frequency values are as a rule captured a cycle when voltage crossing at zero. The classical frequency limits normally selected within acceptable percentage depending on generator and network for example a 60 Hz system are 61.5 Hz for over-frequency values and 58.8Hz for under-frequency values. When these thresholds

exceeded, relays protection generate a trip signal after some time delay. Both under/over frequency setting can be actualized utilizing either a time curve or a fixed time. The setting time can be balanced between 0.16 s for the most noteworthy deviation, and 300 s for the least deviation. For deviations past 95% of appraised frequency, a 0.16 s fixed time delay is utilized. Slight frequency deviations in transmission levels may include frequency annoyance stumbling with this method. Under unfaltering state conditions, DG keeps up moderately consistent frequency because it runs in parallel with the upstream utility network. When islanding occurs, generation and load within the created island are seldom precisely coordinated, which comes about in changes in frequency. Hence, out of limits of frequency can be utilized as an islanding detection parameter. The frequency setting is required to be out of the extent of typical operational limits. In any case, since the frequency does not alter instantaneously, this logic may be not fast enough in the islanding detection. Besides, this strategy depends on a huge control awkwardness to drive the frequency out of the pre-specified limits. Due to deficient affectability, an expansive non-detection zone may exist which may increment the likelihood of island arrangement. Due to these impediments, under/over frequency protection are ordinarily utilized as reinforcement backup relay for islanding detection.

2. *Under/Over Voltage*: Voltages are measured in the phase-to-ground voltages to get the RMS value. Commonly protection voltage settings are set to 1.2pu for over-voltages and set to 0.8pu for under-voltages. Voltage deviation setting can be set utilizing either a time curve or a fixed time. Regularly, the time delay for both over- and under-voltage protection

setting are set to 100ms. Voltage is another imperative parameter commonly utilized for islanding detection. Compared to under/over frequency protections, under/over voltage protections work on the suspicion that there's continuously reactive power changes within the island zone. This imbalance leads to a relative alter within the voltage level, e.g., overabundance of reactive power awkwardness will lead to drive up the voltage and vice versa. Thus, it can be considered as a pointer of islanding. The change of voltage is moderately speedier than the frequency since there's no mechanical dormancy related to it. The limit setting for under/over voltage protection to be exterior the statutory voltage-limits. In case the voltage outperforms these limits, the DG is required to be isolation off. In any case, this strategy may be influenced by numerous other unsettling influences, which can result in disturbance stumbling. Additionally, it can be troublesome to decide islanding situation beneath the circumstance where generation and load are closely matched. As a result, island will not happen unless the variation of load or generation takes the voltage out of limits.

3. *Rate of change*: In this islanding technique, a protection relay is set such that in case the rate of change of frequency is higher than preset setting value, the protection will activate and isolate the generation units. In this method, the set point for the most extremely allowable rate of change of frequency may be basic esteem. It ought to be chosen such that the alter in frequency amid ordinary utility associated operation does not cause an untrue tripping but islanding ought to cause by protection to trip. The trip setting for the protection relay depends on the generation units and load in the network. ROCOF islanding detection strategy is the most commonly

utilized anti-islanding protection procedure, it gives quick discovery and effortless usage. ROCOF is considered one of the most sensitive to the system disturbance in the power network. In this manner, the application of the ROCOF protection relay to distinguish network islanding has been limited.

The rate-of-change in both active and reactive powers may be a sensible marker for islanding detection, considering that, but for an adjusted circumstance, it competes positively for a fast-islanding detection. Through observing the rate of change of power (dP/dt), the value of rate of load power during the islanding situation is much greater than the rate of load before islanding. The active output power of the DG unit will be measured and calculated at any time. The calculation of the power output in the distributed generation units can be calculated by Formula 2.1:

$$P_{DG} = |va||ia| \cos(\theta a) + |vb||ib| \cos(\theta b) + |vc||ic| \cos(\theta c). \quad (2.1)$$

The rate of change of power is calculated with a time subordinate of this power over a period. The issue with this strategy is that in a few cases, such as motor starting, capacitor bank exchanging, the genuine time measured information is mutilated, and this strategy seems cause wrong isolated.

To begin with, the rate of change of power is calculated at any time as shown in Fig. 2.3, in the event that this result is less than the decided limit setting the system is considered ordinary, but in case its value surpasses the limit setting, in this case the capacitor bank of the distributed generation unit gotten to be tripped. When the (RMS) load voltage's value drops to be less than a passable value, at that point this condition is considered to be

islanding and the DG unit must be isolated. Something else, the capacitor bank is switched onto the grid and generation units continuous working.

The advantage of this combination strategy is that indeed in the event that the rate of change of power of detached strategies works inaccurately during system disturbance, the active techniques coordinates with (dP/dt) , and can effectively identify conditions and make fitting choice to isolated.

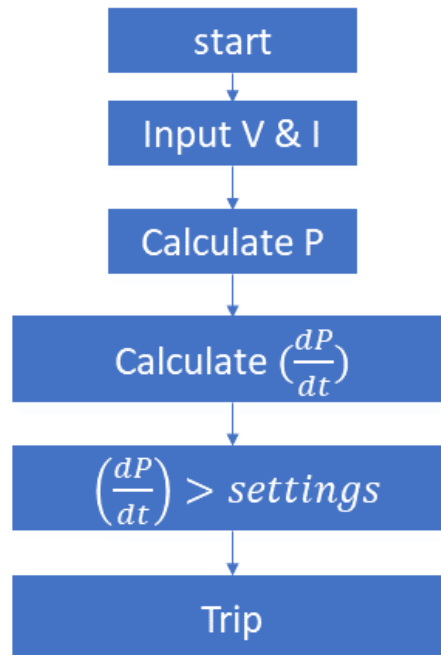


Figure 3.3 Flowchart of Power Change Rate Analysis for Distributed Generation Unit.

The rate of change is usually the foremost commonly utilized strategy to detect the islanding. It is based on the suspicion that there's continuous deviation between the generation and load within the island zone. The

coming power imbalance will provide rise to a fast change of frequency that may overcome the governor's action.

This technique considers the frequency or power change and does not take into account the effect of fault. The (df/dt) protection will be activated if the rate of change reached to the protection setting for the islanding situation. For ROCOF protection, the normal setting values utilized in a 60Hz network system range from (0.1 Hz/s $\rightarrow$ 1 Hz/s) which depends on the quality of the network system. ROCOF is more often than not considered as a touchy and dependable strategy for recognizing islanding conditions. In any case, this hand-off will fall flat to identify islanding when the power deviation between generation and load in the network is small.

In common, ROCOF is considered as an attainable choice for islanding location. Be that as it may, this hand-off endures from the restriction of non-detection zone and cannot give valuable protection when the load-generation lopsidedness within the shaped island is little. Other than that, it may cause intemperate disturbance stumbling due to network transients during load switching due to network faults.

4. *Vector Surge*: Normally, there is shift cycle duration between the measured waveform of the voltage comparing with the reference cycle at each rising zero-crossings of the terminal voltage which is measured by Vector surge (VS) relays. In an islanding circumstance, the cycle term is either longer or shorter, depending on in the event that there's shortfall or abundance of power unbalanced within the islanded zone, refer Fig. 2.4. This variety of the terminal voltage angle ($\Delta\delta$) consider as input parameter to the vector surge protection relay.

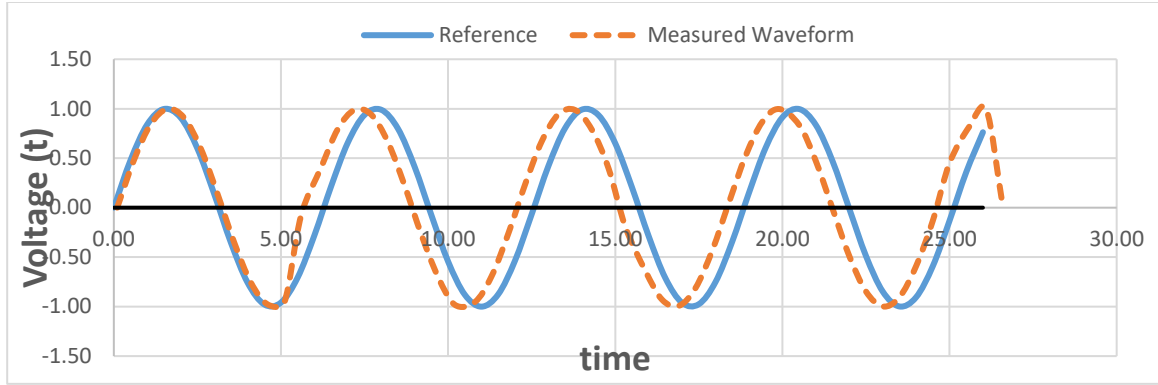


Figure 2.4 Comparison of Measured Voltage Waveform and Reference Cycle Showing Shift in Cycle Duration.

In case the variety of the terminal voltage angle surpasses a pre-specified edge, a trip command is sent to the circuit breaker immediately. Ordinarily, vector surge relay permits this edge to be balanced within the run from ($2 \rightarrow 20^\circ$). Another critical characteristic available in this protection is a blocking function during low terminal voltage. In the event that the terminal voltage drops underneath a flexible level threshold (V_{min}), the trip command from the (V_s), relay is blocked. This is to avoid the actuation of the (V_s) relay during short circuits or generator start-up conditions. This blocking function is to avoid operating the (V_s) relay during short circuits or generator starting conditions.

Vector surge relay can be categorized as a sort of frequency-based relay because of the similitude of this (V_s) principal protection with other frequency-based relay, which are moreover based on the guideline of measuring the cycle term of the voltage waveform. Consequently, it endures from non-detection zone when small unbalanced between generation and load in the islanding situation. Besides, this relay is

vulnerable to organize blame happening on adjoining feeder. Moreover, falsely trigger of the relay may happened during the load switching events at the network transients. To reduce the false trigger, it is required to increase the threshold setting of the relay that may lead to vulnerable non-detection zone.

5. *Voltage Phase-Jump*: In this method the output of terminal voltage of the distributed generation is observed for a sudden change in phase. At the moment of islanding the output current from the DG all of a sudden change. This causes a jump in phase of the DG output voltage due to a change in the voltage drop across the synchronous reactance of the alternator (DG). The greatest reasonable jump in phases is chosen in such a way that switching exchanging doesn't cause an untrue tripping but islanding is recognized.
6. *Harmonic distortion*: In this strategy, the Total Harmonic Distortion (THD) is measured at the interface point between generation and transmission line. The harmonic distortion relay is set to some setting which depend on the generation units and network load type and size. If the Total Harmonic Distortion exceeds the protection setting, then the generation units have to disconnect from the grid. Beneath typical working conditions when the utility grid is associated, the PCC voltage may be a hardened voltage with low THD ($\text{THD} \cong 0$). Moreover, when the utility is connected with load, the Photovoltaics inverter harmonic will flow very low harmonic current and low network impedance which create a little sum of distortion on the point of common coupling voltage at generation side. A prerequisite for network associated PV inverters is to not deliver current with more than (5%) THD of its full rate current. When the utility

disengages the harmonic current that flows to the network load, and since load impedance is bigger than the network impedance, the harmonic current will deliver a high harmonic on the point of common coupling voltage. The alter within the voltage harmonic level can be recognized by the PV inverter network, and on the off chance that the level surpasses setting, the PV inverter control system can prevent the inverter from injecting power. The harmonic detection strategy includes a comparable issue and shortcoming point to the phase jump detection strategy, which is the trouble of setting the limits for dependable islanding detection. It isn't continuously conceivable to discover a limit which identifies islanding and does not lead to a wrongful discovery whereas the inverter is still associated to the utility. The setting must be higher than the anticipated utility voltage THD and lower than the THD that will be created by the inverter within the islanding conditions. It is known that for most network associated inverters the greatest allowable THD of voltage is 5%, so within the case of resistive power load, the point of common coupling voltage harmonic after causing the islanding will be 5%. But on the off chance that the power load isn't simply resistive, the overall harmonic distortion of the point of common coupling voltage after causing the islanding may be less than (5%). The reason for usually due to the truth that the parallel RLC load can act as a channel and evacuates the higher arrange current harmonic that diminishing the voltage harmonic distortion level.

2.2.3 Local Active Islanding Detection Techniques

Active islanding location strategies are compelling and solid that have a littler NDZ compared to passive ones. With active strategies, islanding can be identified indeed beneath conditions of perfect coordinate between generation

and network load, which isn't in case of the passive detection technique. The principle of this method is injection of very small disturbance signals to some parameters like Voltage, Current, Phase angle, or Harmonic at the point of common coupling to become clearer and more noticeable.

Below some of the active detection techniques:

1. *Reactive Error Export*: when the generation unit synchronized with the network, the reactive power flows from grid to generation units that can be measured at point of common coupling. The reactive power rely on will operate when the reactive power flow exceeds the protection setting value. Normally, reactive error export relay interface with the automatic voltage regulator that injects and controls the generator voltage. However, if the exported reactive power longer than limit time period the effective in detecting islanding will occur.
2. *Impedance measurement*: the principle of Impedance measurement technique is injecting a high frequency signal on the distributed generation side terminal and monitoring the significant of the change of the frequency. If the changes of the frequency become high, then the generator will be disconnected from the grid. The result will appear in a perturbation of power that is caused by imposing a disturbance in one of the inverter parameters.

2.3 Machine learning Islanding Detection Techniques

Islanding detection leaned heavily on established methods that relied on physical parameters. These methods such as monitoring frequency and voltage deviations have played a foundational role. However, as power systems evolved to become more complex and dynamic, with renewable

energy sources and decentralized generation, these traditional techniques began to show limitations. Certain islanding conditions, especially those that did not result in marked deviations in measurable parameters could evade detection and necessarily need a new approach.

In today's world of technology, electrical and computer engineering continues to witness unprecedented advancements. One area that has seen immense research interest is the use of machine learning in a multitude of applications. Among these applications, the use of machine learning for islanding detection in power systems has become a topic of considerable focus, with numerous scholarly articles elucidating the subject.

Traditional methods of islanding detection often relied on physical measurements, such as frequency and voltage deviations. While effective in many scenarios, these methods have their limitations. They can be slow to react, potentially missing rapid transitions, or they might fail under certain conditions where these physical measurements do not exhibit distinct changes.

Islanding detection in electrical power systems is a critical function to ensure safety and reliability. Various machine learning techniques have been employed for this purpose. Each of these techniques brings unique strengths to islanding detection, and the choice of method often depends on the specific requirements of the electrical system, the nature of the data available, and the desired accuracy and robustness of the detection system. Below introduction and summery of some articles to how some of these techniques are used in islanding detection:

(1) Neural Network based Techniques

The application of Artificial Neural Networks (ANN) across various scientific and engineering domains has seen significant growth. Within the realm of electrical engineering, a notable focus area has been the utilization of ANNs for islanding detection in power systems. Islanding, a scenario where a portion of the grid remains energized despite disconnection from the main power source, poses safety and operational challenges. Hence, swift and accurate detection of such instances is imperative. Consequently, many researchers have turned to ANNs for their adaptive learning and pattern recognition capabilities. Numerous articles have delved into this intersection of power systems and machine learning, highlighting the importance and potential of ANNs in revolutionizing islanding detection. Active location strategies stand out as particularly compelling and robust, exhibiting a smaller non-detection zone compared to passive methods. With active strategies, islanding can be detected even under conditions of perfect coordination between generation sources.

One of the most widely employed techniques is the feed-forward Artificial Neural Network (ANN). Illustrated in Figure 2.5 is the structure of a feedforward neural network, comprising an input layer, output layer, and several hidden layers in between. Each of these layers comprises multiple parallel nodes. The number of nodes in the input layer equals the number of input features, while in the output layer, it equals the number of classes. The layers situated between the input and output layers are termed hidden layers, and the constituent units within them are referred to as neurons, serving as the fundamental building blocks of the ANN. Each neuron encompasses inputs, scalar weights, a scalar bias, and a transfer function.

At the outset of ANN training, weights and bias parameters are initialized randomly. Subsequently, during each epoch, the model endeavors to fine-tune these parameters until convergence is achieved. This typically involves adjusting the weight matrix to minimize the error function, which is contingent upon the classification error. The derivative of the error function is employed to individually adjust weights, ensuring minimal error. Additionally, the transfer function plays a role in normalizing the input data since most training algorithms are sensitive to the data's scale.

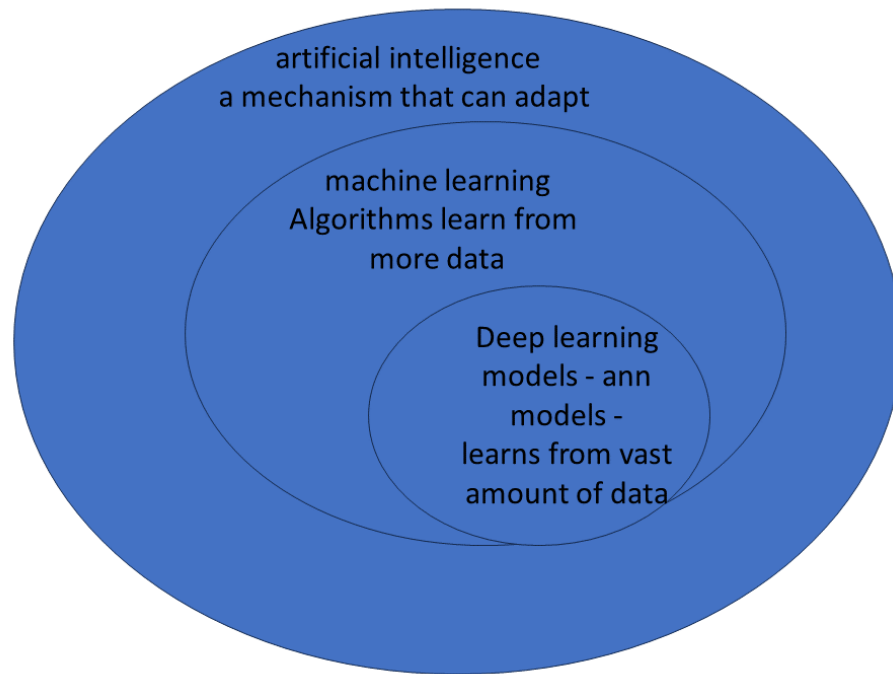


Figure 2.5 Structure of a feedforward neural network.

We proposed to use a fused network of single input simple ANN classifiers to improve the classifier performance. The proposed method consisted of three principal stages: parameter selection, feature extraction and model construction and optimization.

- Parameter Selection

Tenth different local parameters were chosen as inputs for the classification technique after measurement of the local current and voltage waveforms.

- Feature Extraction

In this stage, each input sample denotes the mean value over one cycle for a specific parameter. For every parameter, a sequence of 10 consecutive cycles' mean values is utilized as an input to a moving window. The size of this moving window is directly correlated with the amount of information provided to the classifier and inversely correlated with the speed of classification generation.

In this particular study, after thorough investigation, a moving window size of 10 cycles was selected. This choice was made to optimize performance while maintaining a reasonable time delay suitable for islanding detection limits. A separate data matrix was constructed for each parameter, as depicted in Table 2.1. Within this data matrix, each column represents the moving window of a specific parameter over a period of 10 cycles. Different columns in the matrix represent various event classes.

Given that a set of 10 average values were recorded for each event, ($m = 10$), while N represents the total number of sample sets across various events utilized. A subset matrix for each parameter was assigned as input to a specific neural network for training and validation purposes.

Table 2.1 Organization of input matrix to neural networks.

$Mean_{11}$	$Mean_{12}$	$Mean_{13}$		$Mean_{1N}$
$Mean_{21}$	$Mean_{22}$	$Mean_{23}$		$Mean_{2N}$
$Mean_{31}$	$Mean_{32}$	$Mean_{33}$		$Mean_{3N}$
.....				
$Mean_{m1}$	$Mean_{m2}$	$Mean_{m3}$		$Mean_{mN}$

Instead of using all the parameters as inputs to one large ANN, a separate and simpler ANN was allocated for each parameter. This approach simplified the design of the classifier, improved its performance, and facilitated its optimization.

- Model Construction and Optimization

In this phase, the construction of the feed-forward network was achieved by training neural networks using MATLAB's Neural Network Toolbox. The tan-sigmoid transfer function was chosen for the hidden layer, while the softmax function was applied to the output layer. The scaled conjugate gradient training algorithm was employed for its efficiency in achieving rapid convergence, memory conservation, and suitability for handling large, complex systems. For training and validation, the k-fold cross-validation technique was utilized with ($k = 10$). The concept of 10-fold cross-validation is visually represented in Figure 2.6. This methodology involved randomly partitioning the dataset into 10 subsets, each containing an equal number of various event types. Nine subsets were then utilized for training the network, while the remaining subset was reserved for

validation. This process was iterated 10 times, and the average classification accuracy was computed as the performance metric. The number of neurons in the hidden layer of each network ranged from 1 to 20, and the cross-validation method was applied to optimize the hidden layer's neuron count. This optimization aimed at minimizing misclassification rates while maintaining a reasonably simple neural network structure. Following the optimization of each neural network, their outputs were aggregated into a vector form, and the final classification was determined based on the majority vote output. This ensemble approach proved to yield more accurate and robust results compared to using a single large neural network. The parallel structure of ANNs facilitated the optimization of classification performance by systematically eliminating low-performing ANNs and their associated parameters. This iterative process involved removing ANNs with the lowest accuracy, recording the updated classification performance, and continuing until further elimination resulted in a decrease in classification performance, thereby yielding the optimal structure.

Validation set	Training set	Training set	Training set	Training set	Training set	Training set	Training set	Training set	Training set
Training set	Validation set	Training set	Training set	Training set	Training set	Training set	Training set	Training set	Training set
Training set	Training set	Validation set	Training set	Training set	Training set	Training set	Training set	Training set	Training set
Training set	Training set	Training set	Validation set	Training set	Training set	Training set	Training set	Training set	Training set
Training set	Training set	Training set	Training set	Validation set	Training set	Training set	Training set	Training set	Training set
Training set	Training set	Training set	Training set	Training set	Validation set	Training set	Training set	Training set	Training set
Training set	Training set	Training set	Training set	Training set	Training set	Validation set	Training set	Training set	Training set
Training set	Training set	Training set	Training set	Training set	Training set	Training set	Validation set	Training set	Training set
Training set	Training set	Training set	Training set	Training set	Training set	Training set	Training set	Validation set	Training set
Training set	Training set	Training set	Training set	Training set	Training set	Training set	Training set	Training set	Validation set

Random 1 Random 2 Random 3 Random 4 Random 5 Random 6 Random 7 Random 8 Random 9 Random 10

Figure 2.6 Concept of 10-fold cross-validation.

(2) Fuzzy logic based techniques

Fuzzy logic (FL) could be a computational technique that employs a rule-based approach to illuminate issues instead of numerical modeling approach. The base of those rules is fuzzy logic model which is opposite to the standard conditional rationale that is either 1 or 0, Fuzzy logic describes truth in different degrees. Fuzzy-rule based classifier is utilized for identifying islanding situations. A decision tree (DT) has been utilized to discover the beginning classification boundaries, based on which the participation capacities and the comparing run the show base is created. An active islanding discovery logic based on fuzzy deduction rules is proposed. The proposed strategy employs positive reference in (dq)–synchronous reference scheme. Voltage and frequency at the generation side are utilized as input for the fuzzy logic. Another active strategy based on d-axis infusion strategy for inverter based synchronous DGs that compared to the network associated mode, in islanded mode of operation the unsuitable signals that increase the deviation in frequency. This difference in frequency is utilized to distinguish the islanding situation.

(3) Decision tree based techniques

A decision tree (DT) may be a progressive show which is utilized for classification issues. Decision tree classifier embraces a top-down approach, beginning from the root hub, which contains the introductory classification issue, by recursively part the classification issue into inside hubs that test for different parameters until a classification is accomplished at the leaf hub.

The decision tree-based design acknowledgment classifier has been utilized to classify islanding situations. The proposed islanding detection is based on two factors harmonic reference and rate of change of frequency (ROCOF) at

the generation point of interface with grid. A decision tree classifier utilizes these records to classify islanding states. The execution of the DT based calculation is advanced compared with ANN and SVM based methods and it is detailed that DT classifier performs superior. This calculation makes utilize of energy coefficients of transitory voltage indication that extricated from the target distributed generation.

(4) Naive Bayesian classifier

Naive Bayes (NB) classifier used the principle of Bayes' theorem in calcification technique. NB classifiers accept that the nearness of a specific include in a set is free of the nearness of any other variable in that set. In spite of the truth that highlighting freedom may be a destitute suspicion in most cases, NB classifier regularly performs on standard with other set up classifiers. NB strategy works especially well with huge information sets. An islanding detection procedure is proposed which utilizes NB classifier for classification of islanding occasions whereas approval is done by utilizing support vector machine (SVM) and k-fold cross approval strategies. The proposed procedure has been tried on three distinctive cases:

- a- Inverter based DG,
- b- Synchronous based DG
- c- Multiple DGs.

In the case of inverter DG, NB classifier is detailed to have a classification precision of (82% and 52%). All things considered, NB classifier performed greatly well with Synchronous based DG and Multiple DGs with a detailed precision of nearly (100%).

(5) Support vector machine classifier

Support Vector Machine (SVM) is directed learning calculation, meaning it requires a set of information to prepare and test the logarithm. Once tested, the SVM will utilize kernel techniques to venture the input space to a higher-dimensional include space and recognize the ideal hyperplane that classifies the information with minimum error and highest distance between the hyperplane and closest vector. SVM classifiers are unaffected by the test measurements. Auto-regressive flag modeling is connected to the voltage and current signals at the point of common coupling to extricate a add up to of 62 highlights, which are utilized as an input include vector for the SVM classifier with radial basis function as a kernel. The SVM classifier is very useful for islanding detection, especially during the operation fail of vector surge relay.

(6) Random forest classifier

Random Forest Classifier (RFC) is a gathering learning method that develops numbers of decision trees (DTs) during testing phase, where each DT is developed by utilizing random subset of the real information. After that these DTs are utilized to classify any input information set. In this strategy, DTs are built based on entropy and Infogain, which are assistance utilized to classify islanding situation. The performance of random forest classifier is compared with other classifiers, and it is resulted that random forest classifier has way better in performance in terms of the accuracy of the classifier, non-detection zone and duration of the islanding detection. The following articles explore the innovative application of machine learning techniques in the field of islanding detection within electrical power systems. These studies demonstrate how advanced algorithms and computational models, including

neural networks, fuzzy logic, and various classification methods, can enhance the accuracy and efficiency of detecting islanding events, thereby contributing significantly to the safety and reliability of power grids. The research encapsulated in these articles highlights the potential and versatility of machine learning in addressing complex challenges in energy systems management.

1. A novel neural network with simple learning algorithm for islanding phenomenon detection of photovoltaic systems [15]: The research primarily seeks to devise an advanced method for detecting the islanding phenomenon in photovoltaic (PV) power generation systems, which is crucial for maintaining power system safety and reliability. To emulate this scenario, a simulation environment was established using the PSIM software package, focusing on a (516W PV) array system constructed from photovoltaic modules. The innovative approach to islanding detection is anchored on an extension neural network (ENN). This ENN amalgamates the extension distance concept from extension theory with the multifaceted attributes of traditional neural networks (NN), such as learning, recalling, generalization, and parallel computing. The new brain system (ENN) uses both common and new ways to detect if a solar system is in island mode. It checks for power issues like changes in voltage or power at the power end. They made this brain-like system using computer code written in the C language and used the PSIM program to support it. This code helps the system decide if the solar system is in island mode and then take action.

The extension neural network applied in this research integrates the diverse detection methodologies from both passive and active islanding detection techniques. By doing that, it can analyze power quality disturbances, which

may manifest as voltage swells, dips, power harmonics, or voltage fluctuating at the grid's power end. Such comprehensive analysis is instrumental in determining whether a given irregularity is a simple power quality anomaly or a more serious islanding operation. To realize this, the algorithm for the extension neural network islanding detection was encapsulated in dynamic-link library (DLL) modules. This code, scripted in the *C* programming language and bolstered by the PSIM software package, facilitates the seamless transmission of signals from the DLL back to the primary controller, culminating in complete control over islanding detection. Reinforcing the method's effectiveness, the simulation outcomes consistently indicated that this novel islanding detection mechanism can accurately pinpoint islanding events and ensure that loads are timely and appropriately severed from the PV power generation system within predefined limits. The tests they did showed that their new method can quickly and correctly find out when the solar system is operating in "island" mode and then disconnect devices safely.

2. An Effective Method for Islanding Detection Based on Variational Mode Decomposition [16]: This research introduces a fresh way to detect when power systems are working in island mode using something called variational mode decomposition (VMD). The new method checks the main parts of the electric "song" to see if the system is in "island" mode or not. Using VMD, they break down the power's "song" and look at the energy in each part. Then, they use this information to decide about the state of the power system. Depending on the beats, they decide if everything is normal or if there's an island situation. To test their method, they created a pretend power network on a computer using a program called

PSCAD/EMTDC. They then tried their new VMD-based method on different power situations, like when things are normal, when there's an island. Some situations had "island" mode, some were normal, and others had different power levels or quality issues. The computer tests, or simulations, showed that their VMD-based method is both fast and accurate, even in the toughest tests.

3. *An intelligent islanding detection of distribution networks with synchronous machine DG using ensemble learning and canonical methods* [17]: This research talks about a smart way to detect when power networks, called distribution networks, operate in an island mode using special machines known as synchronous machine DG. They focused on a thing called THD, which deals with the quality of voltage and current in the system. From this, they gathered six special points or features. To decide if the system is in island mode or not, they trained computer programs known as ensemble learning models and canonical methods. Canonical methods, including MLP, SVM, and DT, are good but have some problems. They can get confused with noisy data and can only deal with straightforward information. On the other hand, ensemble learning models, like RF and Ada-boost, are made up of several small learners. They're like a team that works together, making them better at handling complex information. They tested these methods using a dataset made of (220 events) (120) island situations and (100) normal ones. They used (70%) of this data to teach the computer and (30%) to test it. The Ada-boost method was the star, getting everything right (100%) of the time. RF also did well, especially when there was noisy data. When compared to older methods, this new way was both more accurate and simpler. In addition, their

method doesn't impact the system's reliability or quality because it doesn't need any communication.

4. *A New Islanding Detection Technique Based on Passive Parameter using a Combination of Artificial Neural Network and Evolutionary Programming Algorithm* [18]: For power systems like distributed generation (DG), there's a danger called islanding. This happens when a section of the network becomes isolated and operates on its own. For safety, these "islanded" sections should be switched off right away. There are a few ways to detect islanding. One of the latest and most effective ways is using a method called computational intelligence. In this research, they made a new islanding detection method for a special kind of DG. They used Artificial Neural Network (ANN) combined with Evolutionary Programming (EP). ANN is like a computer brain and EP helps fine-tune this brain. First, they looked at 16 different passive parameters, which are like vital signs of the power system. They wanted to find out which of these was the most sensitive or reactive to islanding. After some tests, they picked the best one. This sensitive parameter was then used as a guide for the ANN-EP system. They trained this system using lots of data from a simulation of an (11 kV) power network. They compared the performance of just ANN and the combined ANN-EP. The result was the combo of ANN-EP was much better at figuring out islanding situations.

They found that a specific measure, called $(\frac{df}{dp})$, was affected by changes in the system's active power. This special measure was then used as the guiding info for the ANN-EP computer brain. They made sure their system worked by using a method called (K -fold) cross-validation. This is like double-checking their work. The final results were impressive. The ANN-

EP method was not only good at telling islanding and non-islanding events apart, but its accuracy level was consistent and reliable. The research showed that this new combined approach was a strong and dependable way to detect islanding in power systems.

5. *Evaluating the effectiveness of a machine learning approach based on response time and reliability for islanding detection of distributed generation* [19]: Islanding detection in distributed generation is of utmost importance for ensuring the safety and reliability of power systems. Traditional methods for islanding detection, such as vector surge relay, frequency relay, and rate-of-change-of-frequency relay, often fall short in scenarios with small power imbalances. This limitation prompts the need for a more efficient approach. This study introduces a novel method that utilizes support vector machine (SVM) classifiers to detect islanding events in synchronous distributed generation.

The core principle of this method is featuring extraction from network variables. These features are obtained using a sliding temporal window, tailored to maximize detection rates at a set false alarm rate. To ensure optimal classification, the SVM classifier is trained with different kernels, including linear, polynomial, and Gaussian radial basis function (RBF). The parameters for these kernels undergo meticulous tuning to enhance their classification performance. The proposed approach is used in situations where traditional relays falter, especially under minor power imbalance conditions. When tested against various power imbalance scenarios, the approach displayed adaptability by varying its detection time accordingly. Notably, this paper shows the performance of the proposed machine learning-based method against that of conventional relays,

assessing their relative reliability and response times. The results indicate that the SVM-based method exhibits significant promise, particularly in real-time operational contexts.

The research further refines the SVM-based approach by selecting optimal window-widths from the Receiver Operating Characteristics (ROC) curve, aiming to strike a balance between response time and reliability. Recognizing that the inception time of islanding events isn't always predictable, the study employs a sliding data window with a consistent step size to extract features. This data is then used to classify events as islanding or non-islanding. Subsequently, a decision rule based on majority voting is formulated after analyzing detection rates and false alarms. This paper's contributions are underscored by a comparative analysis with traditional relays. The SVM-based relay (SVMR), developed from the proposed algorithm, outshines conventional systems in terms of both reliability and detection time, confirming its potential as an advanced solution for islanding detection.

6. *Islanding detection method for DFIG wind turbines using artificial neural networks* [20]: Islanding detection in power generation systems is a crucial process that ensures operational efficiency and system safety. This research introduces an innovative passive islanding detection technique specifically designed for wind farms utilizing doubly fed induction generators (DFIG). Instead of relying on traditional methods, this approach taps into the capabilities of artificial neural networks (ANN).

The proposed method hinges on meticulous voltage and current measurements. These electrical signals undergo a Fourier transformation to pinpoint the second harmonic. Subsequently, the symmetrical

components of this second harmonic, derived from the voltage and current signals at the wind farm's end, serve as inputs to an ANN. This neural network is adept at distinguishing between genuine power quality disturbances and actual islanding operations at the point of common coupling (PCC). To demonstrate the method's robustness, simulations were executed through Matlab/Simulink, unveiling its swift and efficient islanding detection capabilities. However, the study also highlights a limitation: the system's effectiveness dwindles when the load values (P&Q) approach or surpass predefined boundaries. In scenarios where the load value diverges significantly from set limits, the method encounters a non-detection zone (NDZ) and consequently cannot discern islanding conditions. Nonetheless, in most operational contexts, this ANN-based method offers a promising alternative to traditional islanding detection techniques, particularly for DFIG wind turbines.

7. *A novel islanding detection technique using modified Slantlet transform in multi-distributed generation* [21]: Islanding detection remains a pivotal aspect of power generation to ensure the reliability and safety of systems, especially in multi-distributed generation units. This research presents an advanced hybrid technique that integrates the capabilities of the modified Slantlet Transform (MSLT) with machine learning to achieve passive time-frequency islanding detection. The core of this approach rests on optimizing the Slantlet Transform's parameters, specifically its scales and decomposition levels, using the Harmony Search Algorithm (HSA) to ensure precise islanding classification.

MSLT plays a vital role in the extraction of salient features from the detection parameters. These features, derived from both islanding and non-

islanding events, feed into machine learning classifiers, which automatically categorize them to enhance the detection rate. An overarching goal of this method is to ensure a robust detection system that reduces unintended interruptions in distributed generation during non-islanding circumstances. The proposed anti-islanding protection technique's efficacy was examined through simulations of various events within a multi-distributed generation system. The results, which shed light on the novel islanding detection approach's proficiency, underlined its potential and paved the way for critical conclusions.

A meticulous signal selection procedure was executed, with the optimization algorithm overseeing the selection process and specification of the best Slantlet scales and decomposition levels. Different operational network conditions underpinned the extraction of optimal signals. The performance of various classifiers, including the RPNN and different SVM kernels, was rigorously evaluated using metrics like detection rate and false alarm rates. Among the tested configurations, the RPNN coupled with the MSLT stood out, achieving a perfect detection rate and eliminating false alarms in both ideal and noisy environments. Furthermore, when comparing the MSLT's efficacy against other transforms like the Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT), and the standard Slantlet Transform (SLT), the MSLT combined with RPNN emerged as superior. Some of the notable advantages of the proposed method include its resilience against noise, rapid training, and enhanced accuracy, all of which are validated by the obtained results.

8. *A novel Multi-LSTM based deep learning method for islanding detection in the microgrid* [22]: Microgrids represent a significant evolution in

energy systems, capable of functioning both connected to the main grid or in an isolated island mode. This adaptability is crucial to renewable energy sources like wind, solar, and hydroelectric power. However, a challenge arises with unintentional islanding in microgrids, leading to issues such as power quality degradation, voltage instability, and potential safety hazards. To solve this, the study introduces a groundbreaking passive islanding detection method (IDM) specifically designed for synchronous and inverter-based microgrids. The solution is utilization of the multi-long short-term memory (multi-LSTM) deep learning architecture, a recent breakthrough in artificial intelligence. By using the harmonic distortion in voltage and current observed at the microgrid's point of common coupling (PCC), the model uniquely accounts for distortions in the main grid across various conditions.

The conducted simulations in MATLAB/Simulink confirmed the method's professionalism, with an impressive average accuracy of (99.3%) and a minimal loss of (0.06). Furthermore, when pushed to its limits with a detection time constraint of (50ms), the multi-LSTM model could still pinpoint islanding events with (97.93%) accuracy, even in challenging scenarios with a power mismatch of less than ($\pm 0.5\%$). This robustness was further demonstrated by applying the model to two hundred novel scenarios, where it achieved an average accuracy of (97.95%). Notably, in these tests, the model's near-zero NDZ (Non-Detection Zone) proved its efficacy, detecting events with (97.93%) accuracy under tight power mismatch constraints. A key advantage is that this method does not compromise the energy system's power quality or stability. The model's true potential was illuminated when pitted against other intelligent

classification methods like Decision Trees (DT), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and multi-layer Artificial Neural Networks (ANN). The multi-LSTM approach, even with minimum input features, surpassed these methods in both accuracy and efficiency. The study concludes with a forward-looking perspective, suggesting that further work could delve into the real-world application of the multi-LSTM for islanding detection, possibly through hardware in the loop (HIL) setups. The results approve for the adoption of LSTM-based deep learning techniques, not just for islanding detection, but potentially for broader fault and power quality analyses, reducing the need for human intervention.

9. *Comparative Study of Different Approaches for Islanding Detection of Distributed Generation Systems* [23]: Unintentional islanding remains a concerning challenge in grid-connected, Distributed Generation Systems (DGS). Islanding detection is crucial due to the variety of Distributed Generation (DG) types and sizes linked to distribution networks and concerns linked to out-of-phase reclosing. The basic and widely used method for this is the passive islanding detection technique. However, this paper introduces two different techniques for detecting islanding conditions. The first is the auto-grounding approach. This method involves applying a three-phase short circuit to the isolated distribution system to reclose the system. In contrast, the second technique harnesses a data mining-decision tree algorithm, particularly effective in distribution systems with multiple DGs. To gauge the effectiveness of both techniques, the Non-Detection Zone (NDZ) was calculated, ensuring they meet the IEEE standards of a 2-second execution time. Upon thorough analysis, the decision tree method emerged as the most effective and precise technique

for detecting islanding states in DGs. The comparison between these methods presents a clear evolution in islanding detection.

The paper emphasizes the importance of accurately and swiftly detecting islanding conditions in DGS. It brings forward the novel auto-grounding technique, which was observed to accurately detect anti-islanding within (1.706) seconds. Meanwhile, the data mining decision tree, a machine learning-based approach, astoundingly identified the anti-islanding condition within a mere (0.162309) seconds, rendering it faster and more reliable than the auto-grounding method. To test these methods, various events were simulated. For the auto-grounding method, (42 events) were used, half being in islanding states and half in non-islanding states. The decision tree method employed (37 events), nearly split between islanding and non-islanding states. The outcomes were insightful: the decision tree method displayed superior accuracy (94.5%) compared to auto-grounding (92.8%). In the ever-evolving complexity of power grid systems, where Distributed Generations and rising power capacities are increasing, rapid protection systems are imperative. A two-second detection time is no longer efficient. Thus, contemporary systems like micro-grids and smart grids demand more advanced islanding detection methods, such as the decision tree method presented, which promises quick detection and high precision.

10. *Data-Driven Islanding Detection Using a Principal Subspace of Voltage Angle Difference* [24]: As power systems increasingly integrate distributed generation, the potential for unintentional islanding events where a section of the grid continues to operate in isolation from the main power source rises significantly. Addressing these scenarios requires the development of

fast and reliable detection methods. This paper introduces a fresh approach towards understanding these incidents by initially examining covariance matrices derived from a simplified power system model. This examination then links to the principal component analysis of covariance matrices drawn from actual experiments. The paper proposed a new islanding detection method that capitalizes on measurements of voltage angle disparities across various system points. Prior to analysis, these angle discrepancies undergo preprocessing to eliminate nonstationary effects. Subsequently, a probabilistic model rooted in principal component analysis gets trained with these processed measurements. The principal and residual, derived from these metrics, become instrumental in distinguishing islanding incidents from other events. The data sourced from the transmission grid, serves to underscore the practicality and efficacy of the method in question.

The study highlights the importance of detrending in ensuring that voltage angle variances maintain a norm, thereby enabling the application of the proposed inferential processes. The paper's principal offering is a cutting-edge, data-driven strategy for islanding detection.

11. *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* [25]: Modern power generation has started leaning towards distributed systems using renewable sources, especially photovoltaic (PV) systems. These grid-linked photovoltaic-based distributed power generation (PV-DPG) systems, however, face the challenge of islanding where parts of the grid operate in isolation unintentionally. Ensuring that these isolated sections can be

detected and quickly disconnected is vital to maintaining power quality, safeguarding equipment, and ensuring both voltage and frequency stability. This paper presents a cutting-edge method to tackle the islanding problem using the tunable Q-factor wavelet transform (TQWT) and an artificial neural network (ANN). Initially, simulations are conducted to calculate essential detection parameters considering various potential grid disturbances, including switching transients and faults. Once these parameters are computed, a decomposition of the resulting signals is performed using TQWT, extracting a range of features from the resulting coefficients. These features, after an optimization process, form the input for the ANN classifier, which classifies islanding and non-islanding states with a remarkable 98% accuracy. The method's efficiency has been demonstrated in both noisy and non-noisy environments, suggesting its potential as a robust solution to detect islanding incidents.

This study shows a unique islanding detection mechanism for PV-connected networks, emphasizing the rapid detection of isolated grid sections. To achieve this, the research simulated potential grid disturbances and used the TQWT to break down the resulting signals into multiple sub-bands. Each sub-band was then characterized using seven distinct metrics. The ANN, equipped with a conjugate gradient algorithm for activation, was tasked with differentiating between islanding and non-islanding events, accomplishing an impressive 98% classification accuracy. Further validation in noisy environments showcased the proposed method's robustness, proving its high accuracy and resilience against external disturbances, highlighting its promise as a future-ready solution for islanding detection.

12.A Novel Microgrid Islanding Detection Algorithm Based on a Multi-Feature Improved LSTM [26]: Islanding detection is paramount for the safe functionality of microgrids. Traditional detection methods present challenges for passive detection struggles with fault thresholds, while for active detection compromises power output quality. This study introduces a sophisticated microgrid islanding detection technique that utilizes the Sliding Window Discrete Fourier Transform (SDFT), Empirical Mode Decomposition (EMD), and an enhanced Long Short-Term Memory (LSTM) network with an attention mechanism. The inverter's output current and voltage at the Point of Common Coupling (PCC) are transformed using the SDFT. Using the symmetrical component method (SCM), specific sequences of voltage and current harmonics are computed and reconstructed. Additionally, voltage and current are decomposed into mono intrinsic mode functions (IMFs). This data is then fed into a deep learning algorithm. An LSTM analyzes the features and classifies them into islanding or grid disturbance categories. The algorithm's accuracy is boosted by the attention mechanism, which assigns weight values to the features, emphasizing the most critical ones. MATLAB/Simulink simulations validated the method, highlighting a remarkable accuracy of 98.4% with a rapid detection time of just (66.94 ms). This system not only enhances accuracy but also reduces non-detection zones and is resilient to noise. Most significantly, it sidesteps the issues of traditional detection methods, ensuring undisturbed microgrid power quality.

This research seamlessly integrates signal processing with an improved LSTM deep learning model for precise microgrid islanding detection. The entire procedure encompasses feature extraction, classification, and

recognition. The innovative aspect of this approach lies in its use of a novel islanding detection index based on harmonic measurements at the PCC and the IMFs acquired through EMD. This multi-feature characteristic significantly augments the algorithm's performance. After training the model with roughly six thousand events, it was found to distinguish islanding occurrences even in challenging conditions with perfect accuracy. Notably, this method effectively tackles the inherent problems of traditional detection techniques and displays remarkable accuracy. This model exhibited robust performance in various noisy settings, minimizing noise interference and bolstering microgrid safety.

13. *Artificial neural network and phasor databased islanding detection in smart* [27]: Islanding is a unique scenario in a power grid where following an outage of one or several transmission lines, the generator keeps powering the local load. This research introduces a novel technique for detecting islanding by leveraging the artificial neural network (ANN) classifier. This classifier is fed with synchronized phasor measurements sourced from a nine-bus power system managed by the Western Electricity Coordinating Council. However, a challenge arises as the phasor data concentrator produces a vast amount of data frames. To address this and optimize the data for the classifier, two methods are applied: the multiplier-based method (MBM) and the Andrews plot-based method (APBM). These methods function for dimension reduction and feature extraction, respectively. Comparative studies against other dimension-reduction algorithms indicate the efficacy of these methods. A notable finding was that classifier accuracy improved with an increase in hidden layers. However, there was an optimal level at which APBM showcased the best

accuracy. The study also evaluated the non-detection zone (NDZ) for APBM. It was observed that upon retraining the neural network, both classification accuracy and detection time underwent changes. A significant advantage of this method is its speed, outpacing other available algorithms, and delivering exceptional accuracy coupled with a reduced NDZ.

Most existing algorithms focus solely on specific accuracy rates, often overlooking average accuracy, this study bridges that gap. A distinctive feature of this paper is its presentation of statistical box plots illustrating the results, a detail commonly missed in other studies. The use of ANNs, fed by time-synchronized advanced measurements, further strengthens the classification accuracy. Both APBM and MBM, the feature extraction methods, are validated as being instrumental to this goal. The algorithms put forth in this research can detect islanding in as little as 0.5 seconds. The average accuracies revealed that the APBM-based ANN methodology stole the spotlight, boasting an impressive maximum accuracy rate of 97.1%. On the other hand, the MBM's corresponding figures were slightly less. This study's conclusions highlight the potential of combining ANNs and phasor data for advancing islanding detection for safer and more efficient power grids.

14. *A New Artificial Neural Network based Method for Islanding Detection of Distributed Generators* [28]: This research paper delves into a cutting-edge artificial neural network (ANN) approach tailored for detecting islanding in distributed synchronous generators. This method lies in its utilization of ANNs as pattern classifiers. This technique can identify islanding conditions solely from voltage waveform samples at the

distributed generator terminals. Such a feature sets it apart from other ANN-based anti-islanding methods and offers a significant edge. A critical aspect of the study was to develop a training data set for the ANN. For this, a strategic data selection procedure was devised to ensure optimal training of the ANN, enhancing the method's efficacy. Furthermore, the research introduced the "time-performance region" concept, which serves as a metric to evaluate the technique's performance, complemented by insights into non-detection zones. The study also encompassed a thorough conversation on data sampling rates to optimize the method, keeping in mind computational demands, thus highlighting its adaptability.

The paper proposes an advanced passive ANN approach for detecting islanding, gauged through non-detection zones across diverse distribution systems and operational states of distributed generators (DGs). The evidence points to the method's superior performance, attributed to ANNs' intrinsic capability of pattern identification. The algorithm is its exclusive reliance on voltage samples from the DG terminals. To streamline the ANN training phase, a novel data selection procedure was rolled out. The system's performance was found to be directly influenced by the active power imbalance in the isolated system. Using the time-performance region and non-detection zones, various ANNs were scrutinized. Among the evaluated ANNs, ANN 128 emerged as the frontrunner, showcasing a staggering (99.88%) success rate within a 2-second detection window, followed by (94.71%) in 1 second and (92.91%) in 0.5 seconds. These figures were especially prominent in challenging islanding detection scenarios characterized by minimal active power imbalances. A standout feature of the method is its robustness, proven by its successful application

in numerous non-islanding disturbances. Impressively, false operation rates remained exceptionally low.

15. *Intelligent islanding detection with grid topology adaptation and minimum non-detection zone* [30]: Islanding a situation where a distributed generator (DG) continues to provide power even when the broader electrical grid has gone offline can pose significant risks especially to utility workers. For the critical nature, multiple techniques have been introduced to detect islanding promptly. This research introduces a new, more intelligent approach for this purpose. At the outset, the S-Transform technique is employed to tap into the frequency spectrum of the three-phase voltage signals and calculate their respective energies. With the energies of each phase in hand, they are passed through a feature selection algorithm to streamline data and reduce its complexity. Following this, an Extreme Learning Machine predictive model processes the refined attributes. The results stand out for their precision compared with other methods. The paper offers an islanding detection mechanism that doesn't heavily rely on computational resources which shows remarkable adaptability concerning grid topology changes. These unique traits mark the technique as perfect for real-time application, given its reliability.

The primary goal is to bolster the protective measures of the electrical power system, with special attention on anti-islanding mechanisms for synchronous generators through an intelligent passive method. The process begins by capturing the frequency spectrum of the voltage right at the DG terminals, utilizing the S-Transform (ST). Artificial Neural Networks (ANNs) are then tasked with event classification. To ensure a swift response and minimize computational demands for the inputs for the ANN.

Performance analysis of the introduced method reveals a significant contraction in the Non-Detection Zone (NDZ). The Extreme Learning Machine (ELM) algorithm emerges superior to the Back Propagation (BP) method, particularly with its reduced NDZ and improved accuracy, even when confronted with a shift in system topology from radial structures to loops. The ELM's accuracy, on average, stands at an impressive 99.80%, and the detection time cuts down to about (26 ms). The paper's crowning achievement rests in its ability to offer reliable islanding protection in grid architecture. It notably stands out in its meticulous examination of the NDZ and the adaptability of an intelligent passive method amidst grid topology changes. Compared to similar studies, this research boasts the smallest NDZ, emphasizing its reliability. However, one limitation is the data volume needed for training intelligent techniques. This research aims to decrease the training data quantity relative to the testing data. Despite its ability to generalize across topologies, integrating more DGs might necessitate retraining the system.

16. *Islanding detection method using ridgelet probabilistic neural network in distributed generation* [29]: Islanding where grid-connected power generation systems continue to operate even after disconnection from the main power grid which poses a range of challenges including safety concerns and issues related to power quality. Thus, the key task is to spot this occurrence, differentiate it from other standard grid disturbances, and swiftly disconnect the Distributed Generation (DG) to counter the mentioned problems. To address this, the study introduces the Slantlet transform as a signal processing tool. Its purpose is to pull out the core features that can help tell apart islanding from standard grid disturbances.

Then, a Ridgelet Probabilistic Neural Network (RPNN) is used for classifying these events as either islanding or a different grid-related interference. Training the RPNN is crucial, and the study offers a novel approach for this: a modified differential evolution (MDF) algorithm. This updated algorithm has a crossover procedure, and a selection process. When tested, the proposed method displayed impressive competence in differentiating islanding situations from typical grid disturbances.

The method specifically evaluates features from the three-phase voltage signals at the Point of Common Coupling (PCC). This helps to differentiate between islanding occurrences and regular grid interferences. To gauge its effectiveness, this technique was trialed using several disturbance signals. This included imbalances in reactive and active power during islanding, and multiple non-islanding disturbances such as voltage sags, swells, nonlinear load switches, capacitor bank switches, and the initiation of motors. The proposed detection mechanism, harnessing the combined power of RPNN and SLT, boasted an accuracy rate of 100% in both standard and noise-affected scenarios. Further comparisons spotlighted the RPNN classifier's superiority over the PNN variant. In another critical aspect of the research, the efficacy of the introduced modified differential evolution (MDE) for training the RPNN was scrutinized. The outcome was clear: the RPNN trained using MDE overshadowed those trained using other statistical techniques in terms of accuracy. Another significant feature of the proposed MDF is its efficiency. It doesn't weigh heavily on computational resources and needs a minimal set of training samples for effective functioning.

17. *Islanding Detection of Microgrid Incorporating Inverter Based DGs Using Long Short-Term Memory Network* [31]: Islanding detection is a crucial aspect of microgrid (MG) operations which ensure the safe and efficient functioning of the system. This paper introduces a novel two-stage method for rapidly detecting islanding events within a microgrid. In the initial phase of this method, the team extracts critical features from voltage and current signals. Through the use of discrete Fourier transform (DFT), these signals are then scrutinized to identify the second harmonic. Following this, the symmetrical components, which include the positive, negative, and zero sequence components, of the identified harmonic for both voltage and current are calculated, resulting in a total of six distinct features. Entering the second stage, the approach employs a deep learning classifier grounded in the long short-term memory (LSTM) network. This classifier's task is to analyze these features and make the pivotal decision regarding islanding. A significant trait of LSTM is its status as a unique type of recurrent neural network, harnessing the power of artificial intelligence in a novel way. To test the efficacy of this method, both simulated and real-world voltage and current signals are utilized. The simulated data is generated using Matlab Simulink, simulating a microgrid equipped with inverter-based wind Distributed Generators (DGs). In contrast, the real-world data originates from an experimental setup, incorporating both wind and photovoltaic DGs. The study then put this method to the test by processing numerous intentional and unintentional islanding events. The results highlight the proposed method's superiority in detecting islanding swiftly, accurately, and reliably when pitted against other prevalent artificial intelligence-based techniques like decision tree (DT), support vector machine (SVM), and artificial neural network (ANN).

The study provides a more profound exploration of the method, emphasizing the importance of the symmetrical components of the second harmonic from voltage and current signals. To guarantee the method's robustness, they incorporate two load models Which the constant power model and the constant impedance model. These models are crucial in ensuring that any power discrepancies or variations in load models do not hamper the proposed LSTM's performance. Furthermore, to guarantee that the method isn't falsely triggered by events unrelated to islanding such as the connection or disconnection of capacitor banks, thorough testing is done. The results show the efficacy of the method, showcasing its edge in terms of accuracy, reliability, and rapid detection when compared to other AI algorithms.

18. *Minimum non detection zone for islanding detection using an optimal Artificial Neural Network algorithm based on PSO* [32]: The islanding detection approaches have been classified into passive and active methods. While passive methods often grapple with a sizable Non-Detection Zone (NDZ), the active techniques tend to adversely impact power quality. Addressing these limitations, this study introduces an innovative islanding detection method, merging the strengths of an Artificial Neural Network (ANN) optimized by Particle Swarm Optimization (PSO) with a straightforward active technique. The combined method seeks to address the potential detections by ANNs due to shifts in the power network's structure. In this refined approach, the ANN continually adapts to changes in the power network and aims to shrink the NDZ. The ANN's optimal parameters including weight coefficients and biases, are determined using PSO, further minimizing the NDZ. Additionally, the paper delves into

comparing the performance of multiple ANN structures Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Probabilistic Neural Network (PNN) when combined with PSO for islanding detection. When subjected to a battery of operational conditions like islanding scenarios, motor initiations, capacitor bank activations, and non-linear load shifts, the method demonstrates its efficacy by correctly identifying islanding operations and steering clear of mal operations in other scenarios and show small NDZ.

The paper accentuates the combined prowess of ANN and the PSO algorithm in detecting islanding events. A standout feature of the proposed technique is its determined focus on shrinking the NDZ to its lowest possible extent. For the ANN, power attributes of Rate of Change of Frequency (ROCOF) and Rate of Change of Active Power (ROCOAP) signals at the Point of Common Coupling (PCC) over five cycles are employed as inputs. Especially notable is the near-perfect accuracy rate of the MLP-PSO when it incorporates two neurons in its hidden layer. Simulated outcomes bolster the claim that MLP-PSO optimally diminishes Mean Square Error (MSE) and enhances the accuracy of ANN in islanding detection scenarios. The ANN's learning process, facilitated by the PSO, operates in real-time, ensuring it remains adaptable and responsive to subsequent changes in the power network's structure.

19. *An Effective Passive Islanding Detection Algorithm for Distributed Generations* [33]: The integration of distributed generations (DGs) into contemporary power systems introduces several challenges, with islanding detection emerging as paramount. In the scenario of islanding, a segment of the power system comprising at least one DG, a passive grid, and a local

load becomes entirely disconnected from the primary grid. While numerous islanding detection techniques have been unveiled in recent studies, there remains a notable concern. These local measurement-based detections grapple with the non-detection zone (NDZ) and may misidentify grid-connected events. Addressing these drawbacks, this study rolls out a novel passive islanding detection algorithm suitable for all DG types. This innovative method harnesses measured data frequency, voltage, current, and phase angle and their rate of alterations at the point of common coupling (PCC). It stands out by accurately pinpointing islanding events, even in cases of precise zero power imbalances. Notably, the algorithm can discern between genuine islanding and non-islanding disturbances like short-circuits, capacitor issues and load shifts without errors.

This study introduces a cutting-edge algorithm tailored for islanding detection within distributed generation setups. The proposed algorithm amalgamates various detection techniques, offering a solution that quickly identifies islanding states. The main feature is its minimal data requirement only needing voltage and current metrics from DG sites to function. This novel algorithm is adept at distinguishing between these faults and genuine islanding events. Its efficacy is showcased across myriad conditions like different fault resistances in short-circuits, varied load connections and compensatory capacitor disconnections. Across all these tests, the algorithm consistently delivers accurate results.

20. *Islanding Detection in a Microgrid using Artificial Neural Network and WT* [81]: Modern microgrid systems face challenges in detecting islanding situations, which occur when a part of the grid operates isolated from the main power source. This paper presents a pioneering approach that

harnesses the power of Artificial Neural Network (ANN) in tandem with Wavelet Transform (WT) for effective islanding detection. Specifically, the method deploys the Daubechies 4 mother wavelet, breaking it down into 5 distinct decomposed levels. The studied microgrid model is comprehensive, comprising a Solar Photovoltaic (PV) system, Wind Energy Converter (WECS), Solid Oxide Fuel Cell (SOFC), and a battery. This system also accommodates linear and non-linear loads. For the detection process, key voltage and current signals are extracted from the Point of Common Coupling (PCC). Islanding detection hinges on the ANN, which is meticulously trained.

The training encompasses both everyday operations and varied fault scenarios. During this process, emphasis is laid on fluctuations in energy levels and standard deviations of the signals obtained. All these analyses are executed on the MATLAB R 2019b platform, employing both its Simulink and M-file functionalities.

The entire analytical process assesses key performance metrics, particularly the energy levels and standard deviations stemming from the 5-level decomposed wavelet. This is meticulously executed across diverse Line to Ground fault scenarios.

The wavelet transform's evaluation underscores its potential to pinpoint islanding situations, regardless of whether the system is under normal operations or facing faults. Conclusive results accentuate the efficacy of employing wavelet transform. It not only adeptly detects but also accurately pinpoints the location of islanding events within the intricate microgrid power setup.

2.4 Comprehensive Management of Islanding Detection in Power Systems

The effective management of islanding detection in power systems is a critical aspect of ensuring the safety and reliability of distributed generation systems. Islanding occurs when a portion of the power grid becomes electrically isolated from the main power system but continues to be powered by local generators like solar panels or wind turbines. This phenomenon poses significant challenges, as it can lead to safety hazards, equipment damage, and stability issues within the grid. The comprehensive management of islanding detection involves the deployment of advanced detection methods, implementation of robust control strategies, and the integration of smart grid technologies to identify and mitigate the risks associated with islanding. This approach not only enhances the overall efficiency and reliability of power systems but also aligns with the evolving dynamics of modern electricity grids, which are increasingly incorporating renewable energy sources.

2.4.1 Technical Management

Technical management in islanding detection is a critical aspect of ensuring the stability and safety of power systems, particularly in the context of the growing prevalence of distributed generation (DG) sources such as solar panels, wind turbines, and other renewable energy technologies. This comprehensive exploration delves into the various facets of technical management in islanding detection, encompassing the deployment of detection methods, challenges faced, integration with power systems, and the evolving landscape of technology in this domain.

At the heart of islanding detection lies the challenge of accurately identifying when a portion of the grid becomes electrically isolated while still being powered by local DG units. The technical management of this detection is complex, as it must be both highly reliable and swift to prevent potential safety hazards and ensure the continuous stability of the power grid. The primary strategies employed can be classified into three categories: passive, active, and hybrid detection methods.

Beyond the choice of detection methods, technical management in islanding detection also involves the integration of these systems into the existing power grid infrastructure. This includes ensuring compatibility with a wide range of DG technologies, adapting to varying grid topologies, and maintaining system performance under different load conditions. It also involves constant monitoring and upgrading of detection systems to incorporate advancements in technology and address new challenges posed by evolving grid dynamics.

The rapid advancement in technologies such as artificial intelligence (AI) and machine learning (ML) is also reshaping the landscape of islanding detection. These technologies offer potential for more sophisticated detection algorithms that can adapt to complex grid conditions and predict potential islanding scenarios before they occur. Technical management in this new era will increasingly involve leveraging these advanced technologies to enhance the accuracy and responsiveness of islanding detection systems.

The technical management in islanding detection is a multifaceted and evolving field. It requires a deep understanding of both power system dynamics and the latest technological advancements. The goal is to ensure

that islanding events are detected promptly and accurately, to maintain the safety and reliability of the power grid, particularly in an age where renewable energy sources are becoming increasingly integral to our energy infrastructure. The effective technical management of islanding detection is, therefore, vital not only for the current stability of power systems but also for paving the way towards a more sustainable and resilient energy future.

2.4.2 Operational management

Operational management in islanding detection is an integral aspect of modern power systems, especially with the increasing integration of distributed generation (DG) sources like solar panels and wind turbines. This field is primarily concerned with the planning, execution, and coordination of activities necessary to effectively detect and respond to islanding events, which occur when a part of the grid becomes isolated but continues to be powered by local DG sources.

A key element of operational management in this context is the development and implementation of robust monitoring systems. These systems are designed to continuously oversee grid parameters and instantly identify any deviations indicative of islanding. This involves deploying advanced technologies such as smart sensors and automated control systems that can swiftly detect islanding events and initiate appropriate responses. The operational team must ensure that these systems are not only accurate and reliable but also capable of integrating seamlessly with various DG sources and the broader grid infrastructure.

Another crucial aspect is the establishment of clear and efficient response protocols. In the event of an islanding detection, operational management

is responsible for orchestrating a coordinated response that ensures safety and minimizes disruption to the power supply. This includes isolating the islanded section to prevent potential hazards, safely shutting down DG units if necessary, and then methodically reinstating normal grid operations. Effective operational management in islanding detection, therefore, plays a vital role in maintaining the stability, reliability, and safety of power systems in an era marked by an increasing reliance on distributed and renewable energy sources.

2.4.3 Economic Management

Economic management in islanding detection is a pivotal aspect of power systems, especially with the increasing adoption of distributed generation (DG) sources like solar panels and wind turbines. This complex field intertwines financial planning, cost-benefit analysis, operational efficiency, and long-term sustainability considerations, underscoring its importance in the energy sector.

The initial investment in islanding detection systems, encompassing both the technology and the necessary infrastructure, represents a significant financial undertaking. These costs include not just the hardware and software but also the integration of these systems into the existing power grid. Further, operational expenses such as maintenance, system upgrades, and staff training add to the ongoing financial commitments. Economic management must judiciously balance these expenses against the potential risks and costs associated with islanding events, which can include equipment damage, efficiency losses, and safety liabilities.

A crucial component of economic management in this context is a thorough cost-benefit analysis. Decision-makers must evaluate the long-

term advantages of investing in robust islanding detection systems against the immediate and ongoing costs. The benefits are manifold: enhancing grid reliability, ensuring safety, maintaining regulatory compliance, and potentially, operational savings through the prevention of grid infrastructure damage or the optimized use of DG resources. In some instances, advanced detection systems might offer operational efficiencies that could offset the initial investment over time.

The broader economic implications of islanding detection extend to electricity pricing and market dynamics. Efficient islanding management can enhance the overall efficiency and reliability of power systems, which can have a downstream effect on electricity prices. As the power market evolves with greater DG integration, the role of islanding detection in maintaining grid stability could become a critical factor influencing market operations and energy trading dynamics.

The economic management in islanding detection encompasses a broad spectrum of activities and considerations. From careful financial planning and cost-benefit analysis to regulatory compliance and long-term sustainability, it plays a crucial role in ensuring the financial viability and reliability of modern power grids. As the energy sector continues to evolve, the economic management of islanding detection will remain a key factor in the sustainable and efficient operation of power systems worldwide.

2.4.4 Reliability in Islanding Detection

Reliability in islanding detection primarily concerns the accuracy and promptness with which islanding events are identified and managed. The goal is to minimize the occurrence of false positives and negatives, ensuring that real islanding events are detected quickly to prevent safety

hazards and maintain power quality. This requires sophisticated detection technologies that can adapt to varying grid conditions and respond appropriately. Passive, active, and hybrid detection methods each have their roles, with their selection and implementation depending on the specific characteristics of the power grid and the types of DG sources integrated.

Challenges to reliability include the dynamic nature of power grids, especially with high penetration of renewable energy sources, which can introduce variability and unpredictability. Additionally, the increasing complexity of power systems, featuring diverse generation and consumption patterns, requires advanced algorithms and models to accurately predict and detect islanding conditions. Reliability also hinges on the continuous monitoring and maintenance of detection systems, ensuring they remain effective over time and under different operational scenarios.

From an operational standpoint, reliability is bolstered through regular system testing and validation, ensuring that all components of the islanding detection system function as intended. Furthermore, the integration of emerging technologies such as artificial intelligence and machine learning offers promising avenues to enhance reliability, providing more sophisticated tools for prediction, detection, and response.

2.4.5 Safety Management

The primary concern with islanding is safety. In the event of a power outage, utility workers might be sent out to repair what they believe to be a de-energized line. If an islanded DG unit is still feeding power into that line, it could endanger the lives of the repair crew. Therefore, immediate

detection and shutdown of these DG units are essential to ensure the safety of utility personnel. Undetected islanded grids pose severe risks to maintenance personnel who might assume the line is de-energized. Engineering management must ensure robust detection systems are in place to prevent such scenarios. Additionally, public safety must be considered, as power quality issues arising from islanding can lead to equipment damage or failures in consumer premises.

Safety in islanding detection is a paramount concern in the field of power systems in the area of growing integration of distributed generation (DG) sources like solar panels and wind turbines. Islanding detection is essential for preventing hazardous situations that can arise when a section of the power grid becomes isolated but continues to operate due to local DG sources.

The primary safety concern in islanding is the risk posed to maintenance and emergency personnel. In an islanding scenario, it is very important to isolate the system fault to save the workers. This poses a severe electrocution hazard. Therefore, the ability to quickly and accurately detect islanding events is critical to ensuring the safety of these individuals. Reliable islanding detection systems are designed to immediately identify such events and either alert operators or automatically disconnect the DG units, rendering the lines safe for maintenance.

The significant safety issue arises from the potential instability of power quality within an islanded zone. DG sources, particularly renewable ones, can produce power with variable voltage and frequency, which may not align with the standards of the main grid. This discrepancy can lead to equipment malfunctions or damage, both within the islanded zone and

upon reconnection to the main grid, posing risks to both infrastructure and end-users. Effective islanding detection systems must rapidly isolate the islanded section to prevent such instabilities from affecting the broader grid and causing widespread issues.

The integration of smart grid technologies presents both challenges and opportunities for enhancing safety in islanding detection. Smart grids, with their advanced communication and control capabilities, can offer more precise monitoring and faster response to islanding events. However, the added complexity of these systems necessitates careful management and regular updates to ensure their reliability in safety-critical scenarios.

Safety in islanding detection is a multifaceted issue that requires a blend of advanced technology, rigorous operational procedures, comprehensive training, and adherence to regulatory standards. As power systems continue to evolve with increased DG integration, the importance of ensuring safety through effective islanding detection becomes increasingly paramount, playing a critical role in protecting personnel and equipment.

2.5 Summary

The introduction highlights the necessity for distributed generation (DG) systems to be disconnected from the main power grid in case of islanding to ensure safety and prevent instability in voltage and frequency. The IEEE standard mandates this disconnection to maintain power quality within acceptable levels.

Islanding detection methods are classified into remote, local, and machine learning techniques. Remote detection relies on abnormal operations sensed by transmission and load utilities, while local detection involves

monitoring generator parameters and comparing them with preset thresholds. Machine learning techniques, such as artificial neural networks (ANNs) and support vector machines (SVMs), offer fast and accurate detection without requiring communication channels or threshold settings.

Effective management of islanding detection is crucial for the safety and reliability of distributed generation systems. Islanding poses challenges like safety hazards and grid instability, necessitating advanced detection methods and robust control strategies.

Integration of smart grid technologies is essential for identifying and mitigating the risks associated with islanding, thereby enhancing overall power system efficiency and reliability, especially in the context of increasing renewable energy integration.

Chapter 3

Dynamic Islanding

Detection Model

Chapter 3 Dynamic Islanding Detection Model

3.1 General

In the pursuit of advancing the integration of renewable energy sources into existing power grids, I have utilized a comprehensive model from an IEEE study, meticulously designed by Ioan Viorel Banu and Marcel Istrate [34]. Their model serves as a fundamental network in my research, offering a robust framework for exploring the dynamics of solar power conversion and distribution. This model epitomizes the intricate process of connecting a 100kW Photovoltaic (PV) Array to a (20kV) utility grid, operating harmoniously at the standard frequency of 50Hz. It encompasses an array of high-frequency power electronic converters and a sophisticated control system that together facilitate the efficient transformation of solar energy into a form that is readily compatible with the power grid infrastructure.

3.2 The Simulink Model of the Grid-Connected PV System

The model I have adopted stands as a testament to Banu and Istrate's visionary work in the field, providing a detailed representation of the key components and their interactions within a grid-tied PV system. It includes a DC-DC step-up converter operating at 5kHz to elevate the DC voltage from the natural output of the PV Array to a higher voltage required for grid interconnection. Additionally, it features a three-phase Voltage Source Converter (VSC) that operates at 2000Hz to convert the DC into high-quality AC power while maintaining unity power factor. The inclusion of a (100kVA) three-phase coupling transformer to step up the voltage to (20kV) showcases the thoroughness with which the model addresses the various aspects of power

conversion and grid compatibility. The IEEE 1547 standard test network as shown in Fig 3.1.

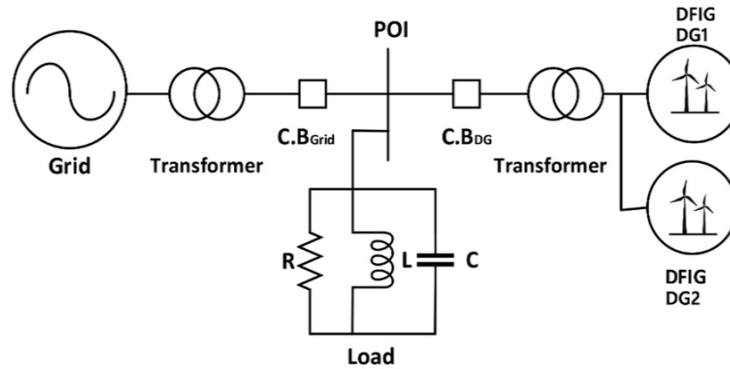


Figure 3.1 IEEE 1547 standard test network (Safdar Raza, 2022)

My study leverages this innovative model to explore and validate the performance, reliability, and efficiency of solar energy systems within the grid, contributing valuable insights into the scalable implementation of renewable energy technologies.

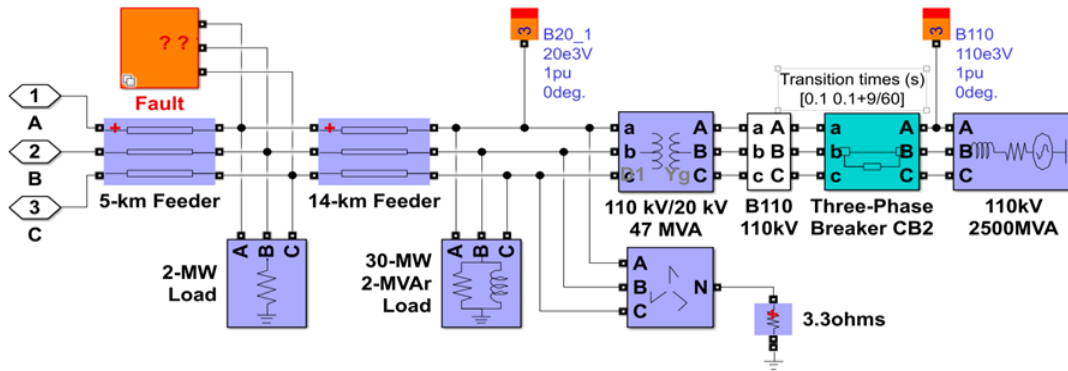


Figure 3.2 Utility grid (20-kV distribution feeder + 110 kV

equivalent transmission system).

The figure presents a detailed model of a solar photovoltaic (PV) system connected to a 20kV utility grid, designed to be simulated in a Simulink

environment. This setup aims to convert solar energy into electrical power that can be used by the grid at the standard frequency of 50Hz. Here's a breakdown of each component and its function within the system:

- 1- 100kW PV Array: This is the primary energy source of the system, comprising multiple solar panels. The PV Array converts sunlight directly into electrical energy, producing a direct current (DC) at its output. The maximum natural voltage of this array is 272V.
- 2- 5kHz DC-DC Step-Up Converter: The step-up converter is used to boost the voltage level from the PV Array's output from 272V to a higher voltage of 500V DC. This is necessary to match the voltage levels required by the grid. The converter operates at a high frequency of 5kHz, which allows for smaller and more efficient components to be used in its construction.

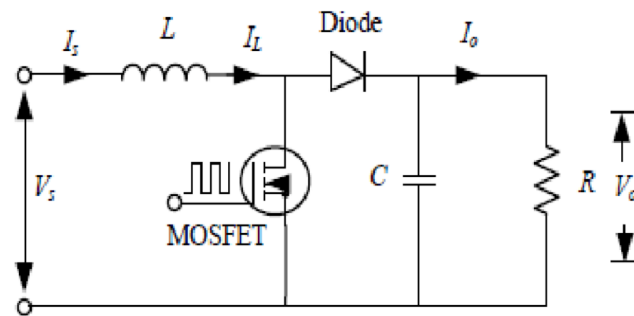


Figure 3.3 DC-DC BOOST converter circuit diagram (Banu, 2014).

- 3- Maximum Power Point Tracking (MPPT) Controller: Integrated with the step-up converter, the MPPT controller optimizes the power output of the PV Array. It constantly adjusts the electrical parameters to ensure that the solar panels operate at their most efficient point, despite the variability in sunlight intensity and temperature.

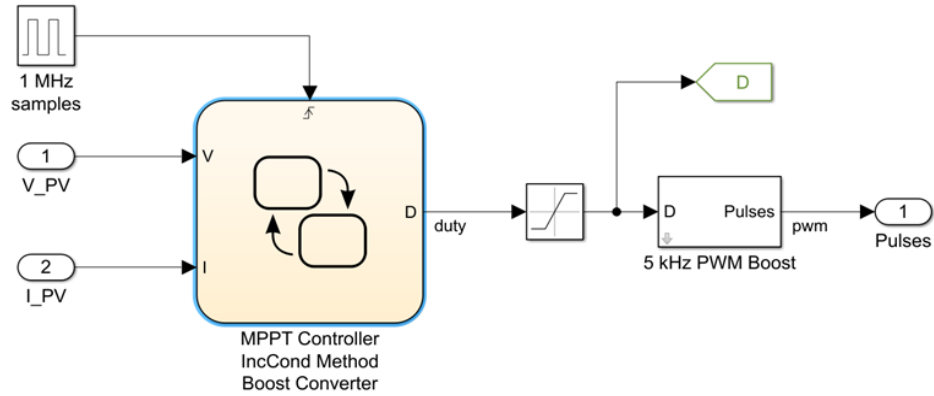


Figure 3.4 MPPT controller layout.

4- 2000Hz Three-Phase Three-Level VSC (Voltage Source Converter):

The VSC is a type of inverter that converts the 500V DC from the step-up converter into three-phase 260V AC. It operates at a frequency of 2000Hz, which allows for high-speed switching and thus a more refined and smooth AC output. The VSC also maintains a unity power factor, which means it adjusts its output to ensure that the voltage and current are in phase, minimizing reactive power and thus inefficiency in the system.

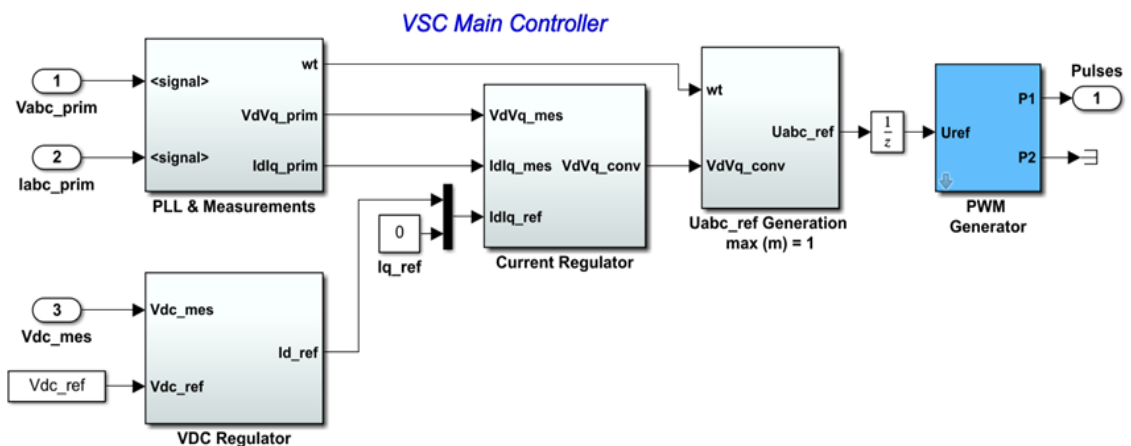


Figure 3.5 Operational Diagram of Three-Phase Three-Level Voltage Source Converter (VSC).

- 5- 100kVA 260V/20kV Three-Phase Coupling Transformer: Once the DC has been converted to AC, it needs to be stepped up to the high voltage level of the grid. This is done by the coupling transformer, which elevates the voltage from 260V to 20kV. The transformer is rated at 100kVA, indicating its maximum power capacity.
- 6- Grid Connection: The final AC output at 20kV is then supplied to the utility grid. The grid connection involves additional protection and control mechanisms (not detailed in the figure) to ensure safe and reliable operation.
- 7- Ancillary Components: The figure also includes ancillary components such as breakers, grounding transformers, and transmission lines, which provide protection, grounding, and connectivity within the system.
- 8- Control and Monitoring: While not explicitly labeled in the figure, the system likely includes a variety of sensors and control units that monitor voltage, current, and power levels, adjusting the operation of the converters and maintaining the overall performance and safety of the system.
- 9- Circuit breakers:
 - a. Three phase circuit breaker CB1 (used to connect PV to Utility grid).
 - b. Three phase circuit breaker CB2 (used to supply loads from utility grid)

Each element in the diagram is critical to the system's operation, converting solar energy into a form that is compatible with the utility grid's requirements.

The high-frequency operation of the converters allows for a more compact and efficient design, while the control systems ensure that the PV Array operates at maximum efficiency, and the AC power delivered to the grid is of high quality.

3.3 The Simulink Implementations of Anti-Islanding Methods

In the evolving landscape of power distribution systems, particularly with the integration of renewable energy sources such as photovoltaic (PV) systems, ensuring reliability and safety has become increasingly complex. The advent of islanding which condition where a portion of the grid continues to power itself despite being disconnected from the main power source poses significant challenges. To address this, advanced protection mechanisms have been developed, each tailored to detect specific anomalies associated with islanding and other grid disturbances. These protection techniques are crucial in maintaining the stability and integrity of the power system.

Various international standards exist globally for connecting Distributed Generators (DG) to the utility grid. These standards impose stringent requirements on islanding detection concerning detection speed, frequency range, and nominal voltage values. They serve as essential benchmarks for the development of new islanding detection techniques. Table 3.1 presents a summary of these international standards for easy reference.

The implementation of these protection mechanisms in MATLAB/Simulink serves a dual purpose. Firstly, it allows for detailed simulation and analysis of each technique under various scenarios, ranging from normal operation to clear islanding conditions. This includes Under/Over Frequency Protection,

Rate of Change of Frequency (ROCOF), Over Voltage Protection, and several others, each designed to monitor and respond to specific parameters of the power system. Secondly, the data generated from these simulations is invaluable for the field of machine learning.

Table 3.1: International standards for anti-islanding.

Standard	Detection time	Frequency range	Voltage range
<i>IEEE 929-2000</i>	<i>Within 2s</i>	<i>59.3–60.5 Hz</i>	<i>0.88–1.1 p.u.</i>
<i>IEEE 1547</i>	<i>Within 2s</i>	<i>59.3–60 Hz</i>	<i>0.88–1.1 p.u.</i>
<i>IEC 62116</i>	<i>Within 2s</i>	<i>59.3–60 Hz</i>	<i>0.88–1.15 p.u.</i>
<i>UL 1741</i>	<i>Within 2s</i>	<i>59.3–60.5 Hz</i>	<i>0.88–1.1 p.u.</i>
<i>UK G83/2 0.5 (DGs up to 16A/phase)</i>	<i>Within 0.5s</i>	<i>47.5–51.5Hz (stage1) 47–52 Hz (stage2)</i>	<i>0.87–1.1 p.u.(stage 1) 0.8–1.19 p.u.(stage 2)</i>
<i>UK G83/3 (17kW/ph or 50kW/3-ph)</i>	<i>Within 0.5s</i>	<i>47.5–51.5Hz (stage1) 47–52 Hz (stage2)</i>	<i>0.87–1.1 p.u.(stage 1) 0.8–1.19 p.u.(stage 2)</i>
<i>Canadian C22.2 No107-01</i>	<i>Within 2s</i>	<i>59.5–60.5 Hz</i>	<i>0.88–1.06 p.u.</i>
<i>German VDE 0126-1-1</i>	<i>Within 0.2s</i>	<i>47.5–50.2 Hz</i>	<i>0.88–1.1.5 p.u.</i>
<i>French ERDF-NOI-RES 13E</i>	<i>Instantly</i>	<i>49.5–50.5 Hz</i>	<i>0.88–1.06 p.u.</i>
<i>Japanese JIs</i>	<i>Within 2s (active IDM) 0.5–1s (passive IDM)</i>	<i>Setting value</i>	<i>Setting value</i>
<i>Korean</i>	<i>Within 0.5s</i>	<i>59.3–60Hz</i>	<i>0.88–1.1 p.u.</i>
<i>Saudi Arabia</i>	<i>Within 0.5s</i>	<i>57.4–62.5 Hz</i>	<i>0.88–1.15 p.u.</i>

By feeding a diverse range of simulation data into machine learning algorithms, we can develop models that predict, detect, and optimize the response of these protection systems under a myriad of operating conditions. The integration of machine learning with these protection techniques a new development in power system management. It promises enhanced reliability, faster response times, and a more adaptive power grid, capable of handling the complexities introduced by renewable energy sources and evolving load demands. This model provides a comprehensive overview of each protection mechanism as shown in Figure 3.6, their implementation in MATLAB/Simulink, and the potential of machine learning in revolutionizing power system protection.

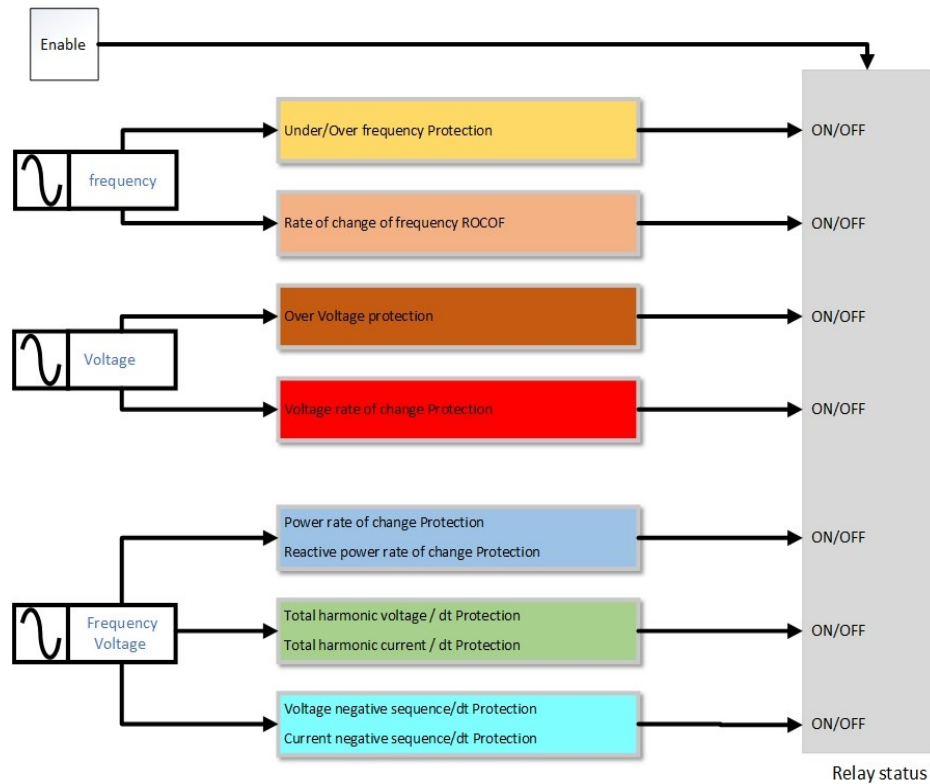


Figure 3.6 Protections Relays of Anti-Islanding Methods.

To simulate each of the listed protection mechanisms in MATLAB/Simulink for the purpose of generating a dataset for machine learning, It will need to create individual Simulink models that accurately represent the behavior of each protection technique under various conditions. The below is detailed explanation of each protection technique listed in the model:

1. Under/Over Frequency Protection: This mechanism is designed to detect when the frequency of the electrical system deviates beyond preset limits. Under-frequency protection is activated when the frequency falls below a certain threshold, indicating a potential islanding condition or other system issues. Over-frequency protection, on the other hand, is triggered when the frequency exceeds a certain limit, which can also be a sign of islanding or system imbalance.

The changes in the frequency can be calculated by the following equation 3.1:

$$\Delta f = f_{DG} - f_{Load} \quad (3.1)$$

f_{Load} is frequency in grid

f_{DG} is frequency at the output of DG

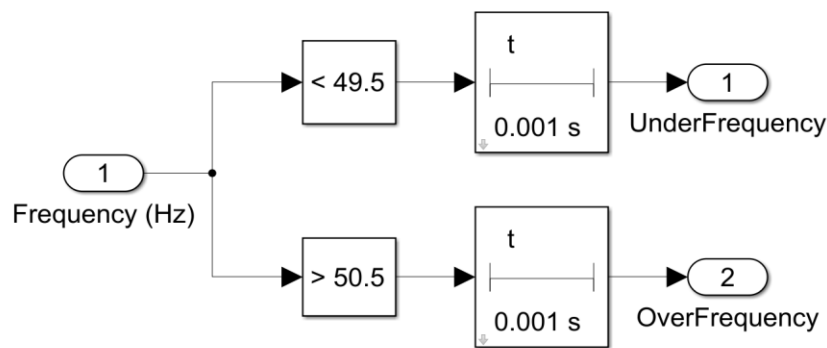


Figure 3.7 Block Diagram of Frequency Deviation Detection Mechanism: Under-Frequency and Over-Frequency Protection.

2. Rate of Change of Frequency (ROCOF): ROCOF protection is used to monitor the rate at which the system frequency is changing. A rapid change in frequency can indicate the disconnection from the main grid, a key characteristic of islanding. This protection scheme is sensitive to sudden frequency variations.

The rapid changes in the rate of frequency which are caused by the imbalance of the power can be calculated by the following equation 3.2:

$$\frac{df}{dt} = -\left(\frac{P_{Load} - P_{DG}}{2H \cdot S_{DG}}\right) \times f_r \quad (3.2)$$

where:

P_{Load} is Load in islanding.

P_{DG} is load of the output of DG.

H is Inertia constant of generator.

S_{DG} is DG rating.

f_r is rated frequency.

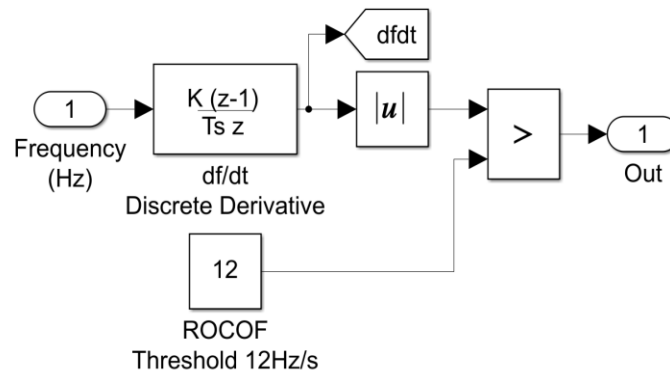


Figure 3.8 Block Diagram of Rate of Change of Frequency (ROCOF) Protection:
Monitoring System Frequency Variations for Islanding Detection.

3. Over Voltage Protection: Over voltage protection is employed to detect unusually high voltage levels in the system, which can occur during islanding scenarios when the local generation and load are mismatched.

The changes in the frequency can be calculated by the following equation 3.3:

$$\Delta V = V_{DG} - V_{Load} \quad (3.3)$$

V_{Load} is Voltage in grid

V_{DG} is Voltage at the output of DG

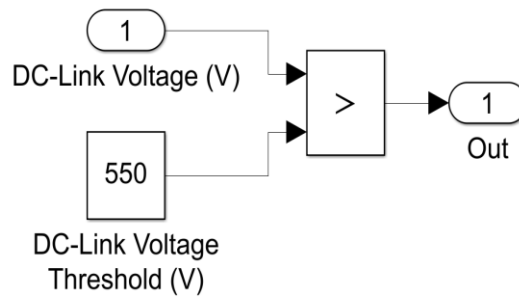


Figure 3.9 Block Diagram of Over Voltage Protection System.

4. Voltage Rate of Change Protection: This technique monitors the rate at which the voltage changes. Similar to ROCOF, a rapid change in voltage can be indicative of islanding or other abnormal system conditions.

The rapid changes in the rate of voltage which caused by the imbalanced of the reactive power can be calculated by the following equation 3.4:

$$ROCOV = \frac{dV}{dt} \quad (3.4)$$

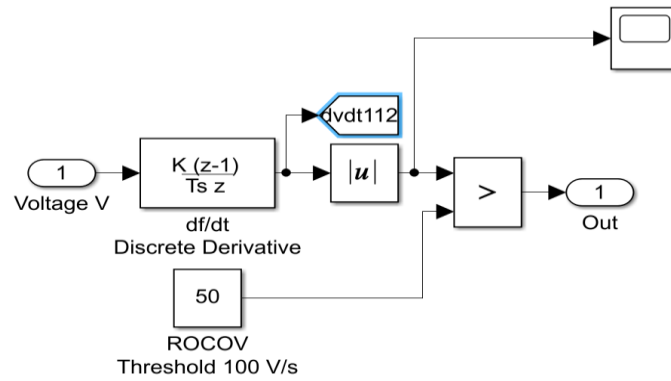


Figure 3.10 Block Diagram of Voltage Rate of Change Protection System.

5. Power Rate of Change Protection: This protection monitors the rate of change in power, both active and reactive. Sudden changes in power levels can be a sign of islanding, as the local generation might not be perfectly balanced with the local load. The changes in the Power can be calculated by the following equation 3.5 :

$$\Delta P = P_{DG} - P_{Load} \quad (3.5)$$

P_{Load} is Load in islanding

P_{DG} is load of the output of DG

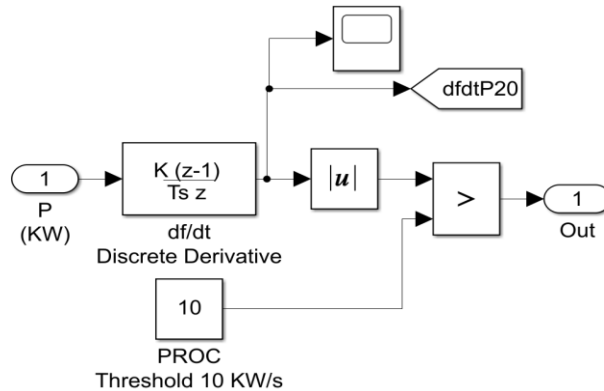


Figure 3.11 Block Diagram of Power Rate of Change Protection System.

6. Reactive Power Rate of Change Protection: Specifically focuses on the rate of change of reactive power in the system. Rapid variations in reactive power can also indicate islanding conditions. The changes in the Power can be calculated by the following equation 3.6:

$$\Delta Q = Q_{DG} - Q_{Load} \quad (3.6)$$

Q_{Load} is Reactive Load in islanding

Q_{DG} is reactive load of the output of DG

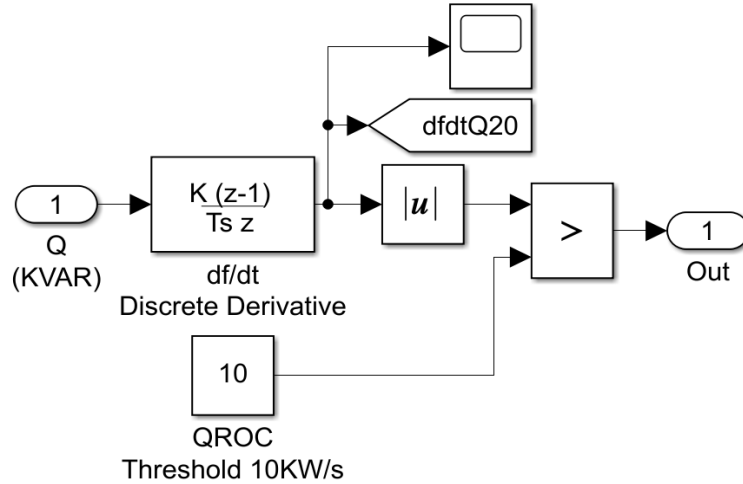


Figure 3.12 Block Diagram of Reactive Power Rate of Change Protection System.

7. Total Harmonic Voltage / dt Protection: This mechanism monitors the rate of change of total harmonic distortion in voltage. Harmonic levels can vary significantly during islanding, making this an effective detection method.

The Total Harmonic Voltage can be calculated by the following equation 3.7:

$$THD_V = \frac{\sqrt{\sum_{n=2}^{\infty} V_{N_{rms}}^2}}{V_{fund_rms}} \quad (3.7)$$

where:

THD_V is Total Harmonic Voltage

$V_{N_{rms}}$ is the RMS voltage

V_{fund_rms} is harmonic voltage

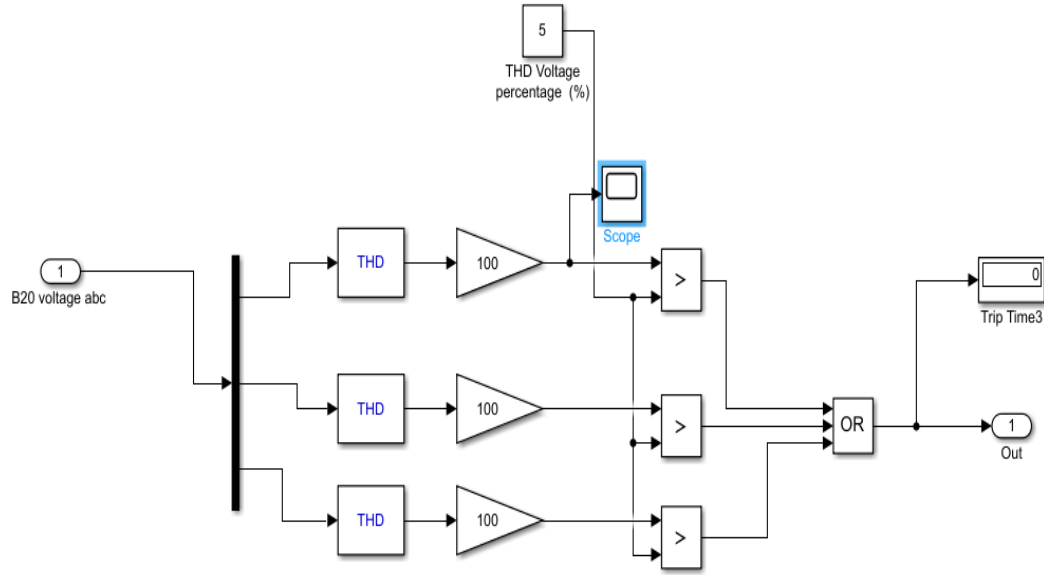


Figure 3.13 Block Diagram of Total Harmonic Voltage / dt Protection System.

8. Total Harmonic Current / dt Protection: Similar to voltage harmonic protection, this technique focuses on the current aspect. It detects rapid changes in the total harmonic distortion in current, which can occur during islanding.

The Total Harmonic Voltage can be calculated by the following equation 3.8:

$$THD_I = \frac{\sqrt{\sum_{n=2}^{\infty} I_{N_rms}^2}}{I_{fund_rms}} \quad (3.8)$$

where:

THD_I is Total Harmonic Current

I_{N_rms} is the RMS Current

I_{fund_rms} is harmonic Current

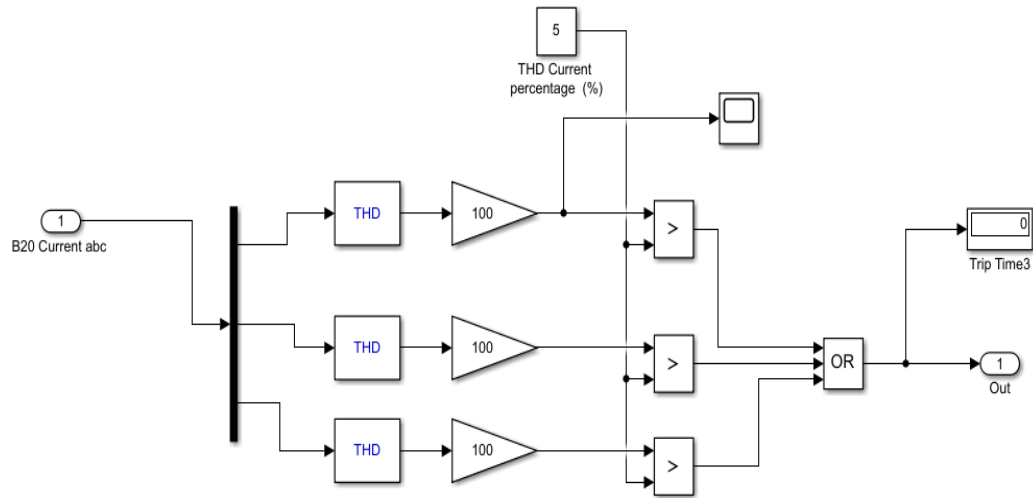


Figure 3.14 Block Diagram of Total Harmonic Current / dt Protection System.

9. Voltage Negative Sequence/dt Protection: This protection scheme monitors the rate of change of the negative sequence component in voltage. Negative sequence components can increase during islanding due to unbalanced conditions.

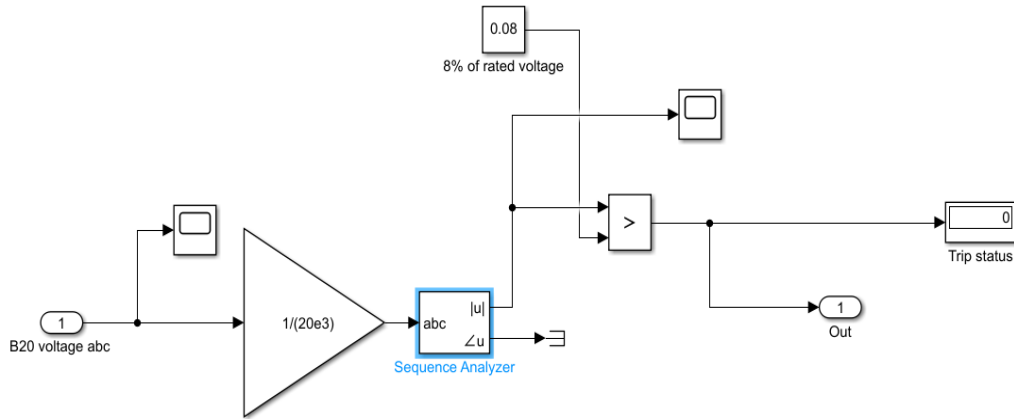


Figure 3.15 Block Diagram of Voltage Negative Sequence/dt Protection System.

10. Current Negative Sequence/dt Protection: Similar to voltage, this method focuses on the rate of change of the negative sequence component in current. An increase in negative sequence components in current can also be indicative of islanding.

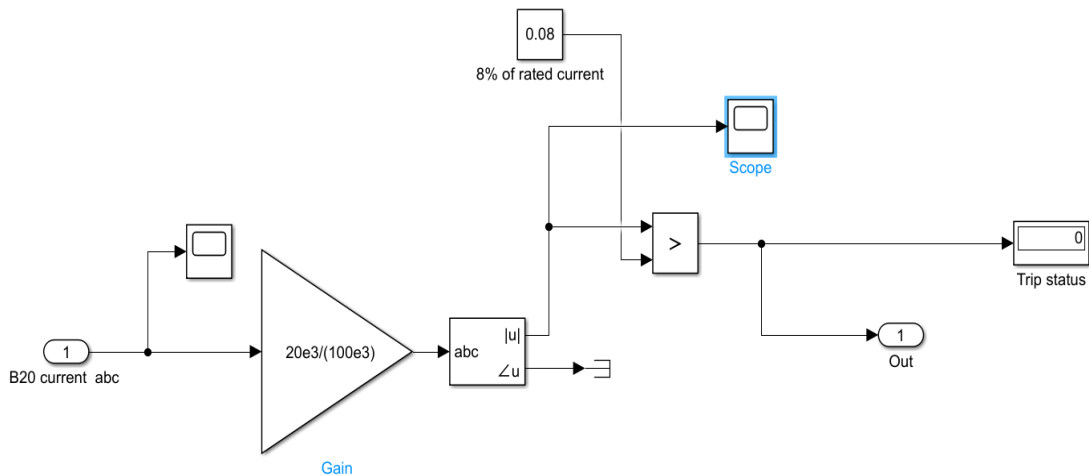


Figure 3.16 Block Diagram of Current Negative Sequence/dt Protection System.

For each of these models, we should vary the input conditions to simulate normal operations, marginal conditions, and clear islanding scenarios. This will provide a comprehensive dataset for machine learning, encompassing a

wide range of scenarios that the protection mechanisms might encounter in real-world operation. These simulation data can be used to train machine learning models to predict, detect, or optimize the response of these protection systems under various operating conditions.

3.4 Different scenarios discussion in the model

Islanding represents a condition in which a portion of power system that includes both load and Distributed energy Resources (DER) remains energized while isolated from grid. The isolation is implemented through a point of common coupling (PCC). The system should be stable against faults that could result in islanding. Rate of Change of Frequency has become the most commonly used method of islanding protection. Other protection relays such as over/under frequency are also used to detect Islanding phenomena.

In the dynamic realm of photovoltaic (PV) system management, understanding the intricate interplay between local load and generation is crucial. The seminal study by Ioan Viorel Banu and Marcel Istrate, published under the aegis of IEEE, offers a comprehensive exploration of this subject through three distinct scenarios. Each scenario provides valuable insights into the behavior of PV systems under varying load conditions, contributing significantly to our understanding of efficient and reliable system management. The meticulously analyzed by Banu and Istrate, not only enhance our understanding of PV system behavior under different load conditions but also underscore the importance of tailored system management strategies. By dissecting each scenario, the study contributes valuable data and insights, paving the way for more efficient and robust PV system designs and operational protocols.

3.4.1 Scenario 1 Local load is greater than local generation

In this scenario, we examine the frequency fluctuations and their Rate of Change of Frequency (ROCOF), or df/dt , under islanding conditions.

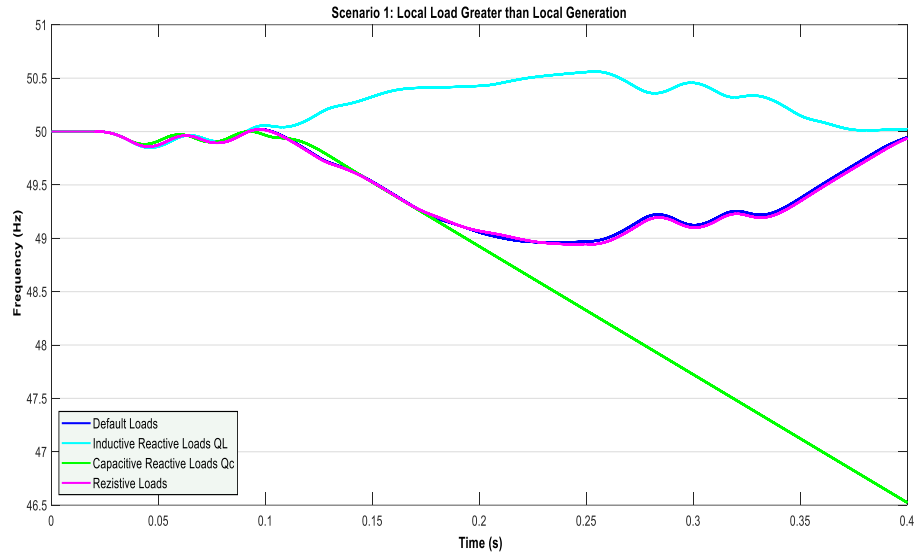


Figure 3.17 Scenario 1: Graphical Representation of Frequency Trends When Local Load Surpasses Local Generation (Banu, 2014).

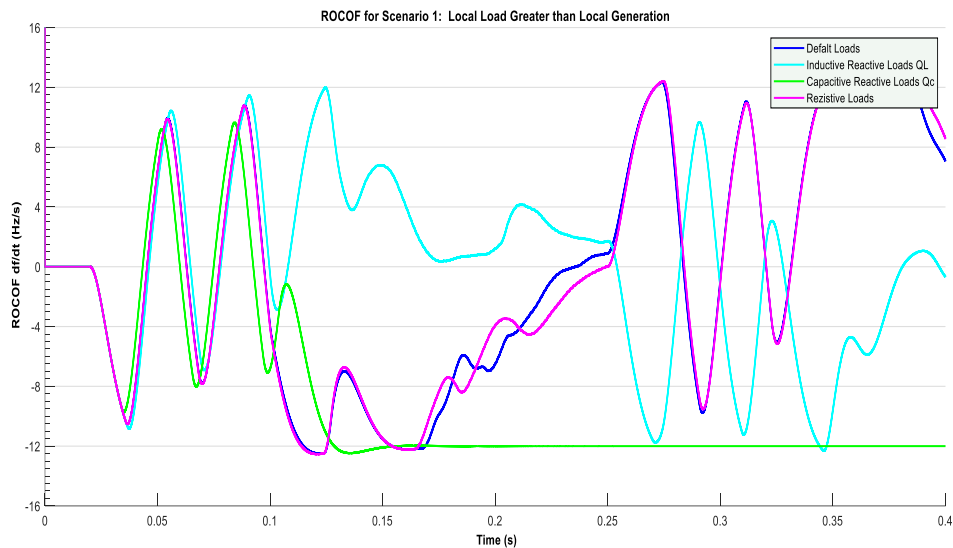


Figure 3.18 Scenario 1: Graphical Representation of ROCOF When Local Load Greater than Local Generation (Banu, 2014).

These are detailed in Figures 3.17 and Figure 3.18, corresponding to various configurations of connected feeder loads. The analysis reveals that for standard and resistive loads, the frequency and ROCOF values exhibit similar behaviors. However, a notable deviation occurs with capacitive reactive loads, where the PV inverter struggles to maintain frequency control.

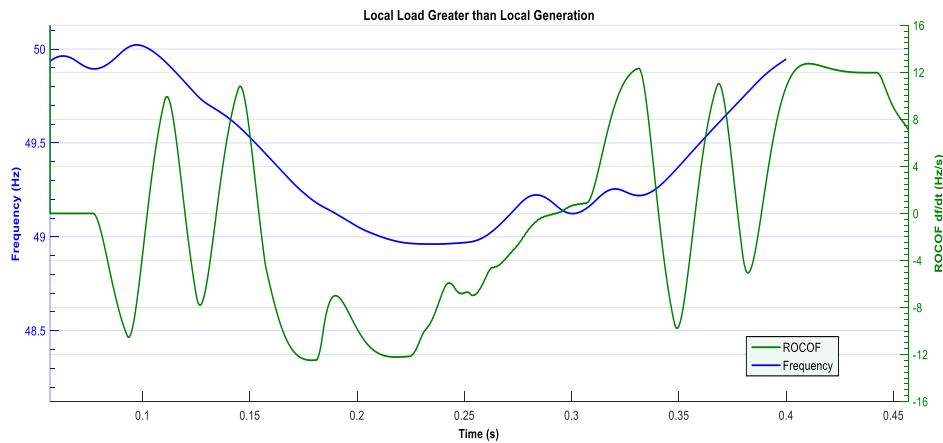


Figure 3.19 Scenario 1: Graphical Representation of Frequency and ROCOF When Local Load Greater than Local Generation (Banu, 2014).

Figure 3.19 integrates the data, showcasing the relationship between frequency and ROCOF during the islanding of the PV system with default utility grid loads. A key observation from this figure is the significant impact of frequency variation during islanding. Specifically, there is a rapid decrease in frequency in a short duration, indicating a direct correlation with ROCOF variations. The critical point for islanding detection is identified when the ROCOF surpasses a threshold of -12Hz/s , with the negative sign indicating a frequency decrease. This insight is crucial for understanding the dynamics of the PV system under specific load conditions and highlights the importance of monitoring these parameters for effective islanding detection.

3.4.2 Scenario 2 Local load matches with load generation

In Scenario 2, we delve into a situation where the local load precisely matches the local generation within a PV system. The pivotal element of this analysis is depicted in Figure 3.20, which illustrates the simulation results for the dc-link voltage under these specific conditions. A crucial aspect of this scenario is the comparative analysis between frequency fluctuations and dc-link voltage variations, particularly in the context of active power management. The results unambiguously demonstrate that variations in the dc-link voltage are more readily detectable compared to frequency changes. This is primarily due to the dc-link voltage exhibiting a more pronounced slope and a wider range during islanding conditions.

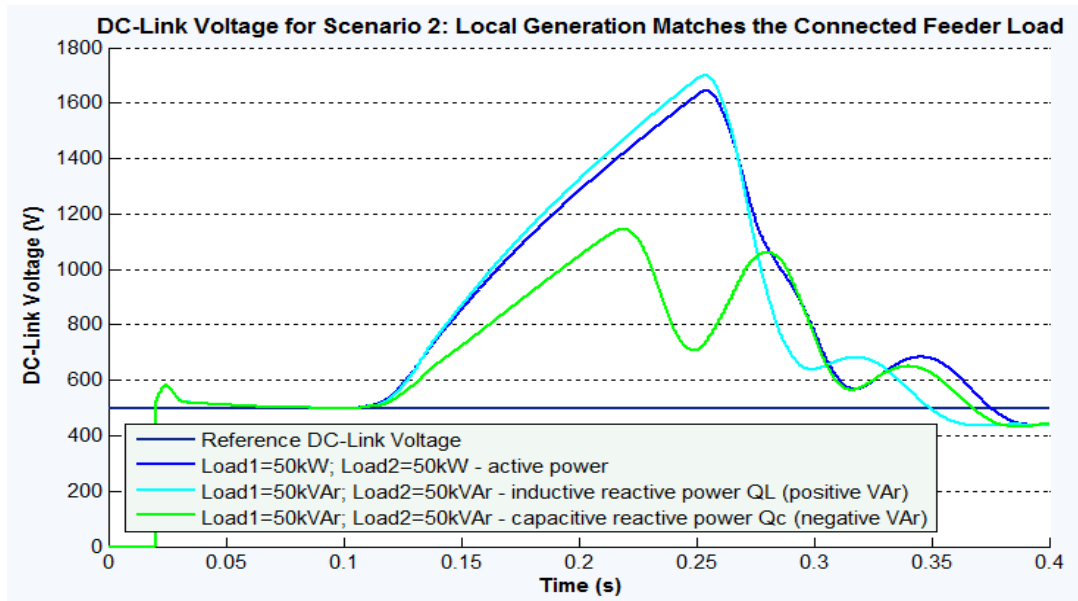


Figure 3.20 DC-Link Voltage during island conditions of scenario 2. (Banu, 2014).

Such findings underscore the significance of closely monitoring dc-link voltage in addition to frequency. The distinct behavior of dc-link voltage under islanding conditions which is characterized by its larger slope and range provides a more conspicuous indicator than frequency variations. This insight

is instrumental in enhancing the detection and management of islanding conditions in PV systems, where maintaining equilibrium between local load and generation is critical.

3.4.3 Scenario 3 Local load less than generation

Scenario 3 presents an intriguing case in power system dynamics where the local load is less than the local generation, a situation often encountered in PV systems. This scenario is illustrated in Figure 3.21, which specifically showcases the variations in dc-link voltage under these conditions.

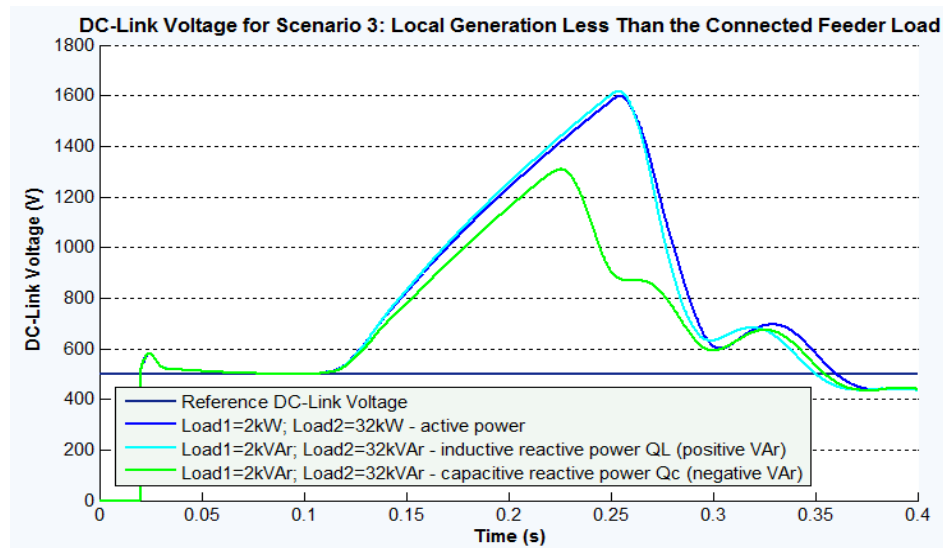


Figure 3.21 DC-Link Voltage during island conditions of scenario 3. (Banu, 2014).

A significant observation from this scenario is the similarity in the results when comparing network configurations and connected loads that are equal to or less than the PV generation capacity. This finding suggests a consistent pattern in the dc-link voltage behavior under varying load conditions, provided the load remains below the generation threshold. Such consistency in dc-link voltage variations is crucial for understanding and managing power systems with excess generation capacity. It indicates that despite variations in

the load, as long as it does not exceed the generation, the system exhibits predictable and comparable voltage behaviors. This insight is vital for the strategic management and optimization of PV systems, especially in scenarios where generation capacity outweighs the demand.

3.5 Model Faults study

Before delving into the specific cases outlined in the table, it's important to understand the different types of electrical faults that can occur in power systems. These faults are critical in understanding and simulating power system behavior, especially in the context of protection and reliability. The five types of faults mentioned are:

Phase-Ground Fault: This type of fault occurs when one of the phase conductors comes into contact with the ground or a grounded object. It's one of the most common types of faults and can cause significant current imbalances in the system.

Phase-Phase Fault: A phase-phase fault happens when two phase conductors come into contact with each other. This type of fault can result in a short circuit between the phases and typically leads to a high current flow in the involved phases.

Phase-Phase-Ground Fault: This is a more severe type of fault where two phase conductors and the ground are all involved. It combines aspects of both phase-phase and phase-ground faults and can lead to complex fault currents and system instability.

Three-Phase Fault: Considered one of the most severe types of faults, a three-phase fault occurs when all three phase conductors are short-circuited

together. This fault type can lead to very high fault current levels and severe disturbances in the power system.

Three-Phase-Ground Fault: This fault involves all three phases and the ground. It is similar to the three-phase fault but with the added complexity of ground involvement, leading to even more challenging conditions for the power system protection mechanisms.

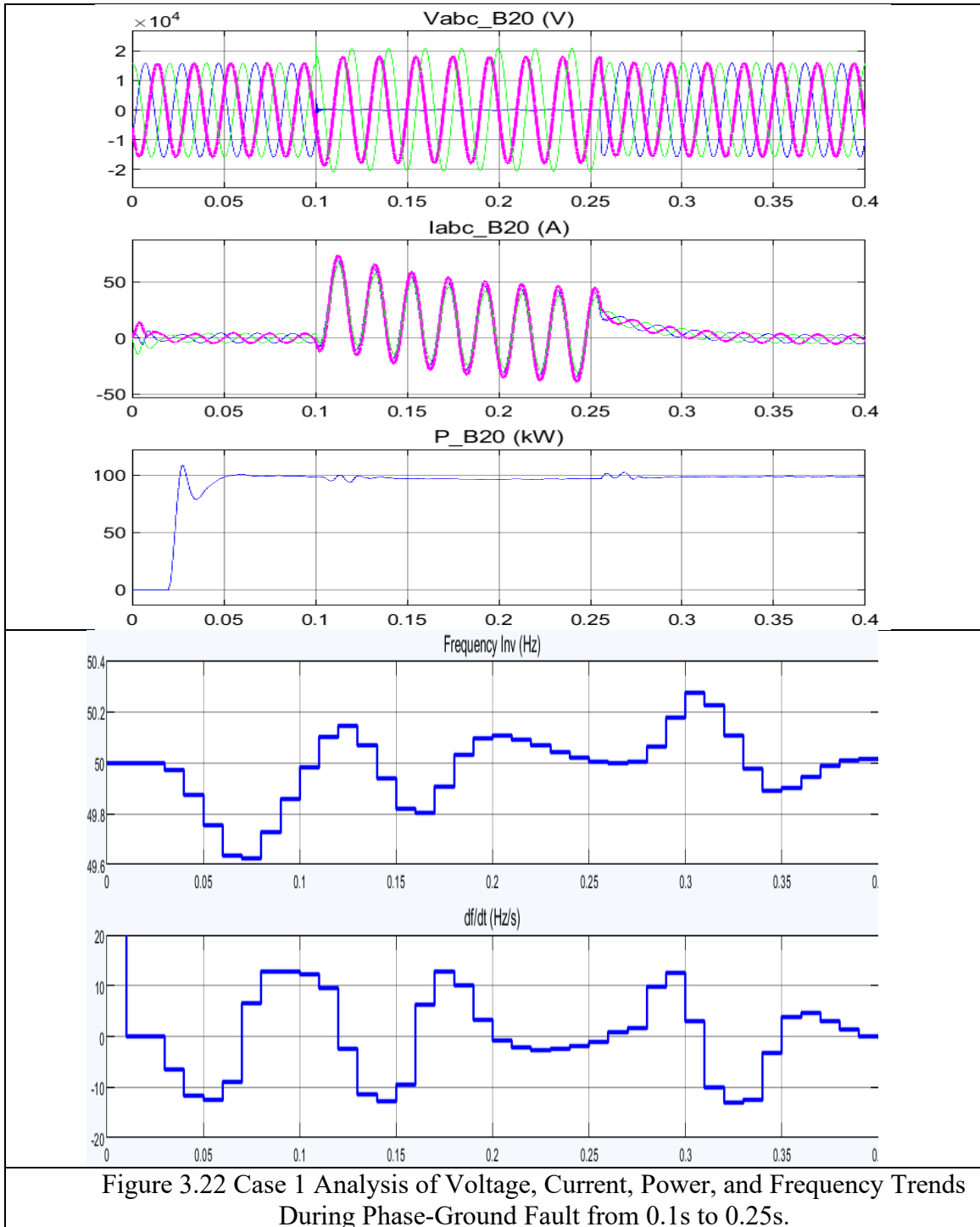
Table 3.2 Three cases simulate with all fault's phases.

<i>Fault type</i>	<i>Phase-ground</i>	<i>Phase-phase</i>	<i>Phase-phase-ground</i>	<i>Three phase fault</i>	<i>Three phase-ground</i>
<i>Cases 1</i>	<i>CB1&CB2 Both OFF</i>	<i>CB1&CB2 Both OFF</i>	<i>CB1&CB2 Both OFF</i>	<i>CB1&CB2 Both OFF</i>	<i>CB1&CB2 Both OFF</i>
<i>Case 2</i>	<i>CB1&CB2 Both ON</i>	<i>CB1&CB2 Both ON</i>	<i>CB1&CB2 Both ON</i>	<i>CB1&CB2 Both ON</i>	<i>CB1&CB2 Both ON</i>
<i>Case 3</i>	<i>CB1:OFF & CB2: ON</i>	<i>CB1:OFF & CB2: ON</i>	<i>CB1:OFF & CB2: ON</i>	<i>CB1:OFF & CB2: ON</i>	<i>CB1:OFF & CB2: ON</i>

Now, let's explore the three cases from the provided table:

Case 1: In this case, both circuit breakers CB1 and CB2 are turned off. This setup allows for the simulation of the system's response in a completely isolated state, with no power flow from the external grid. It's particularly useful for analyzing the system's internal dynamics and the effectiveness of protection mechanisms under isolated conditions.

A. Fault type: phase-ground Fault time: (0.1s to 0.25s)



B. Fault type: phase-phase Fault time: (0.1s to 0.25s)

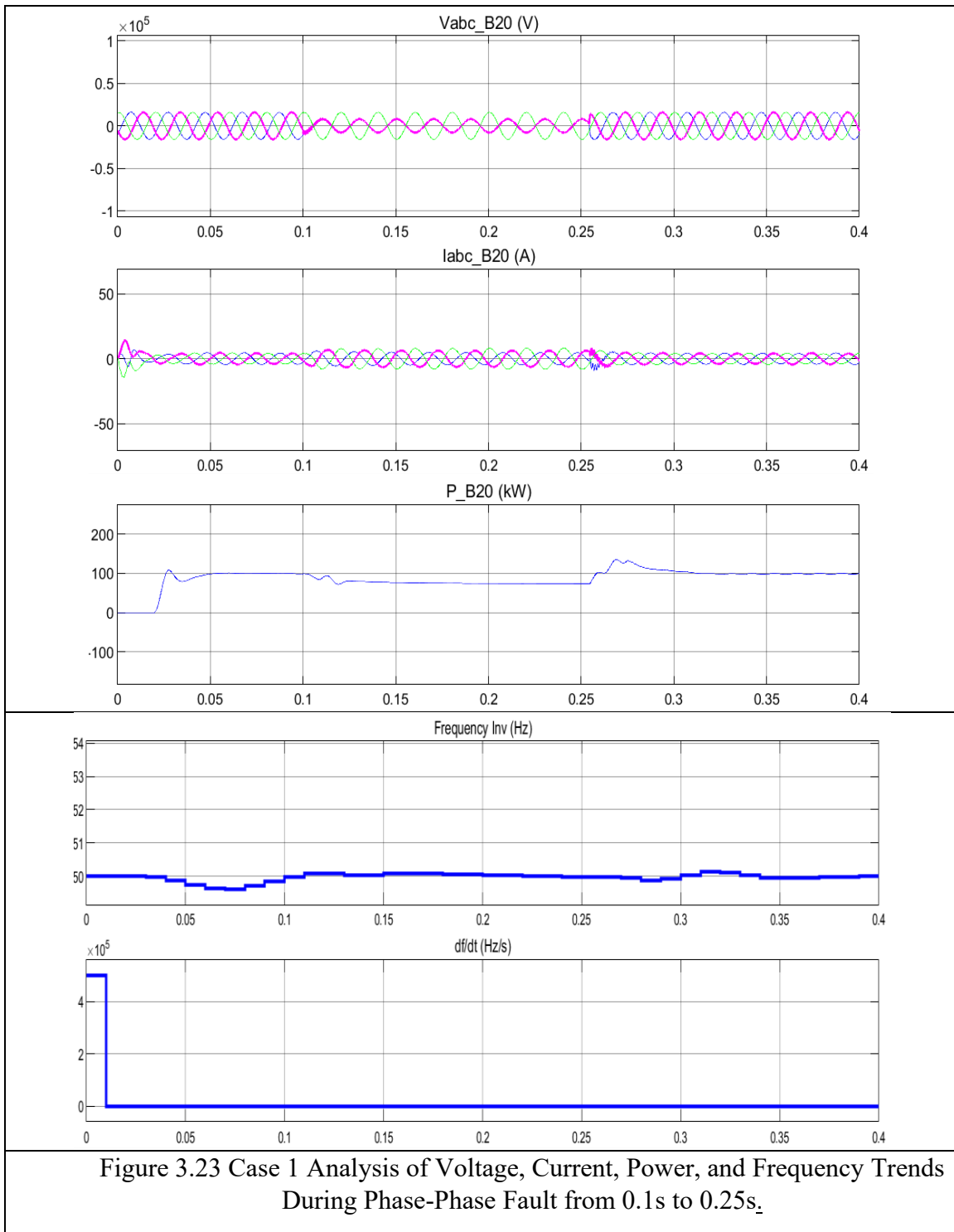
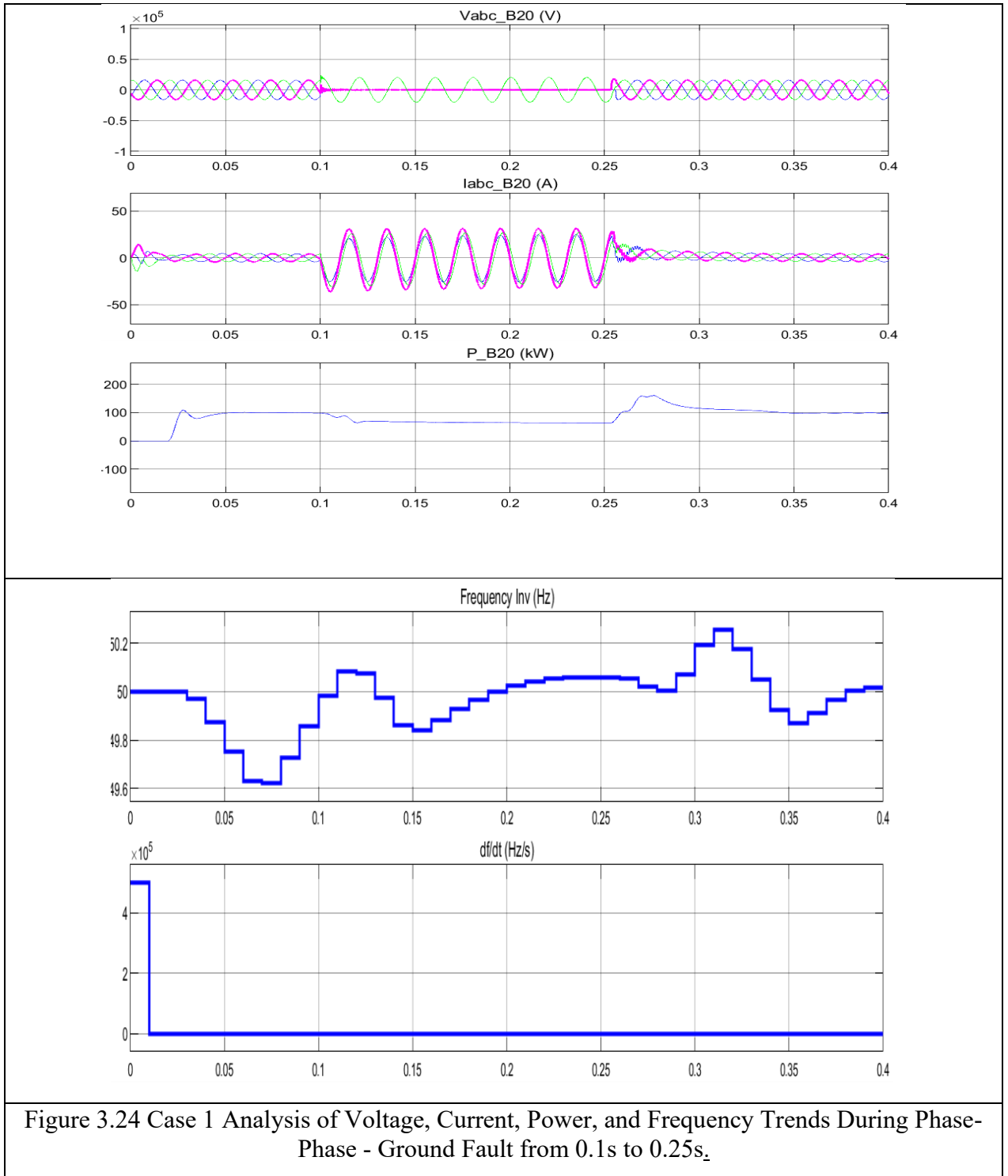


Figure 3.23 Case 1 Analysis of Voltage, Current, Power, and Frequency Trends During Phase-Phase Fault from 0.1s to 0.25s.

C. Fault type: phase-phase- ground Fault time: (0.1s to 0.25s)



D. Fault type: Three-Phase Fault (time: 0.1s to 0.25s)

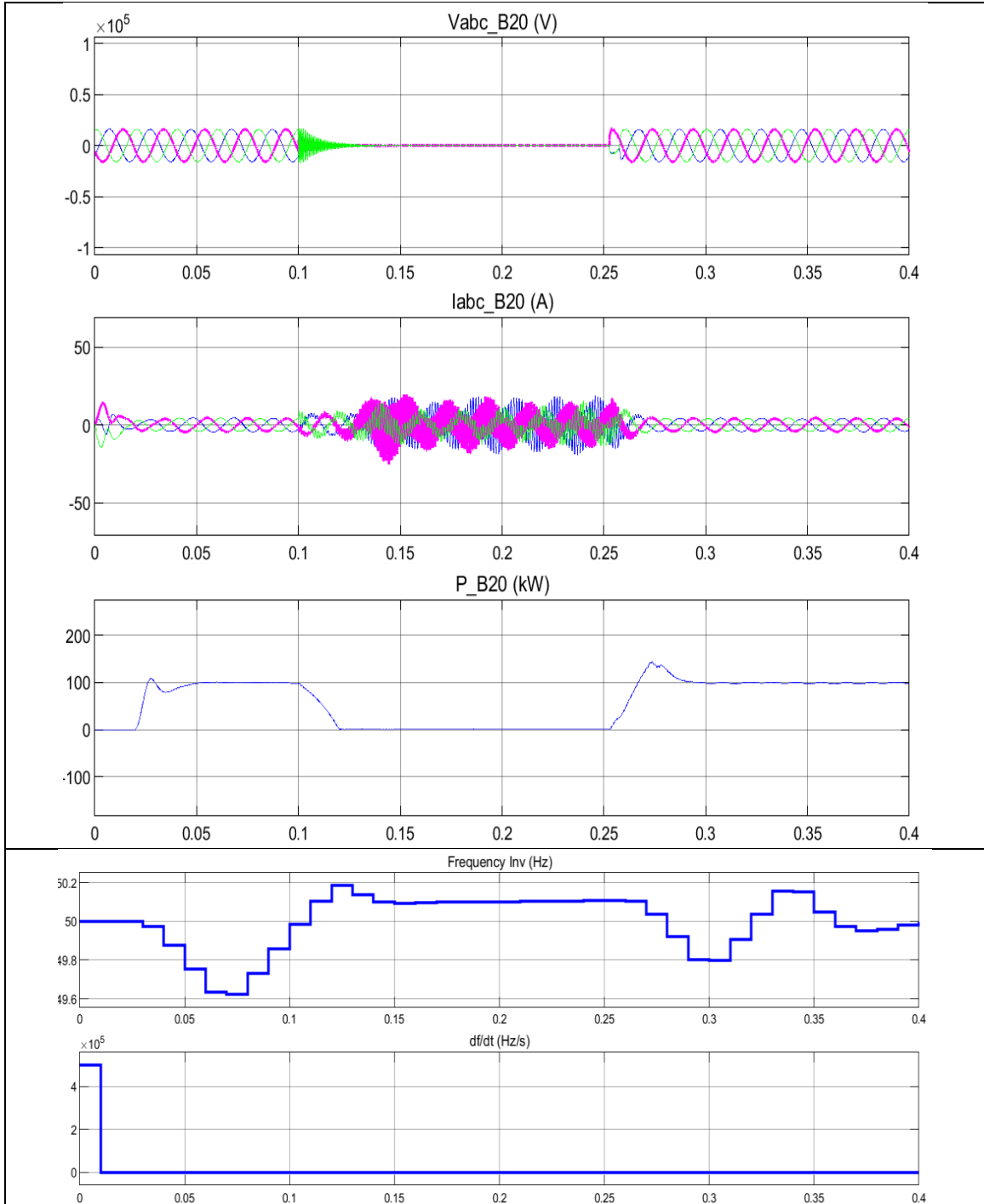
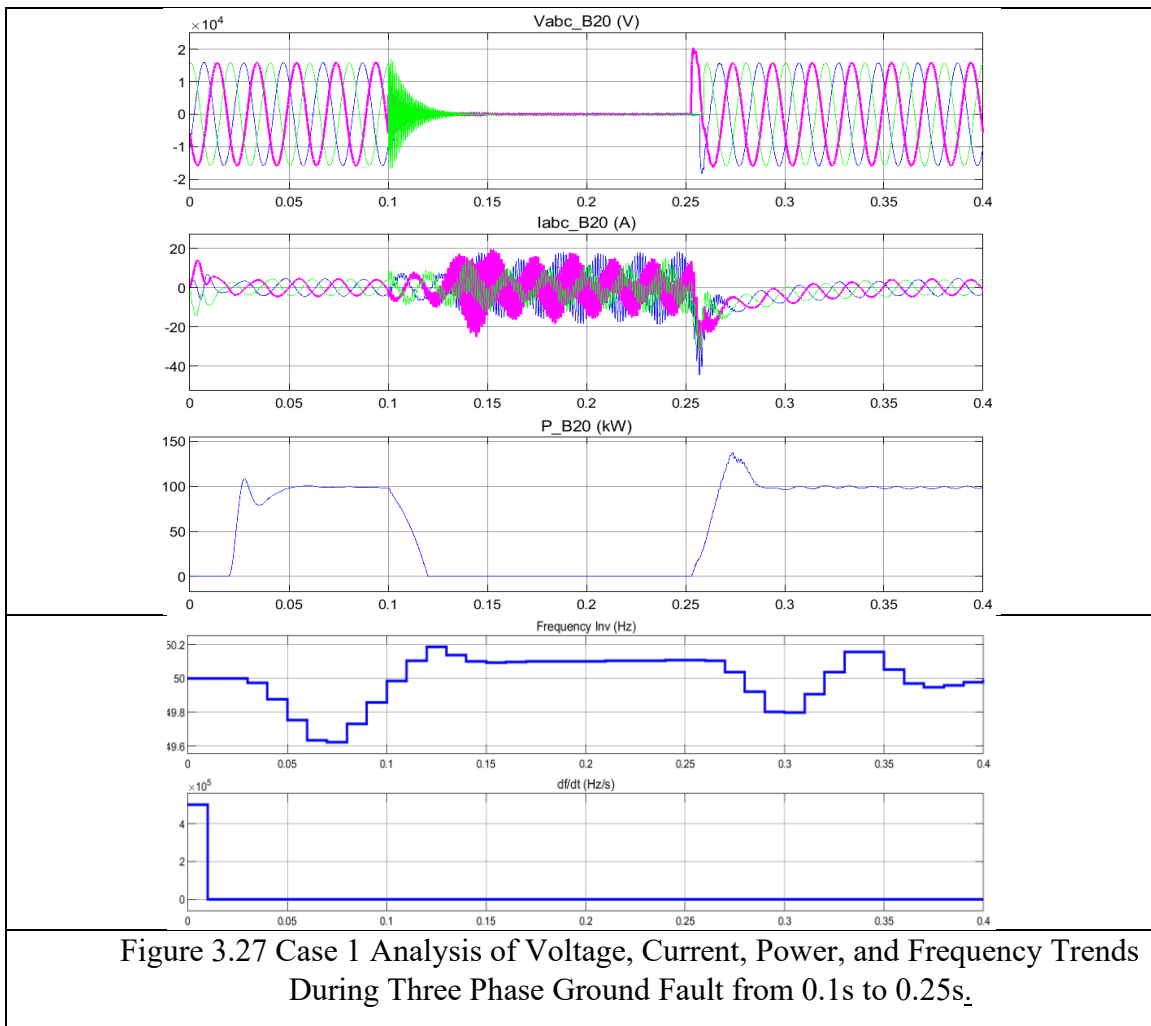
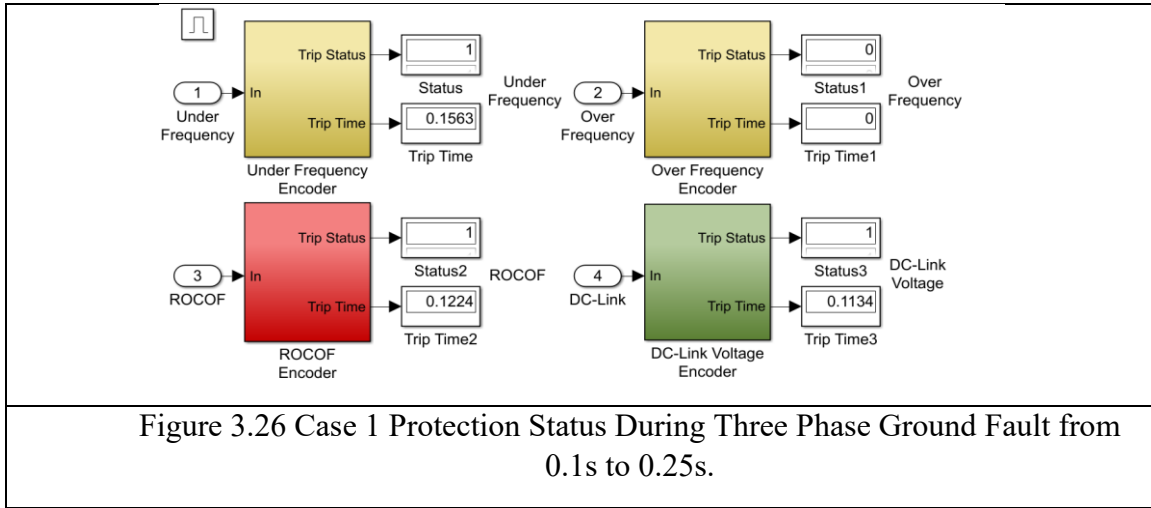


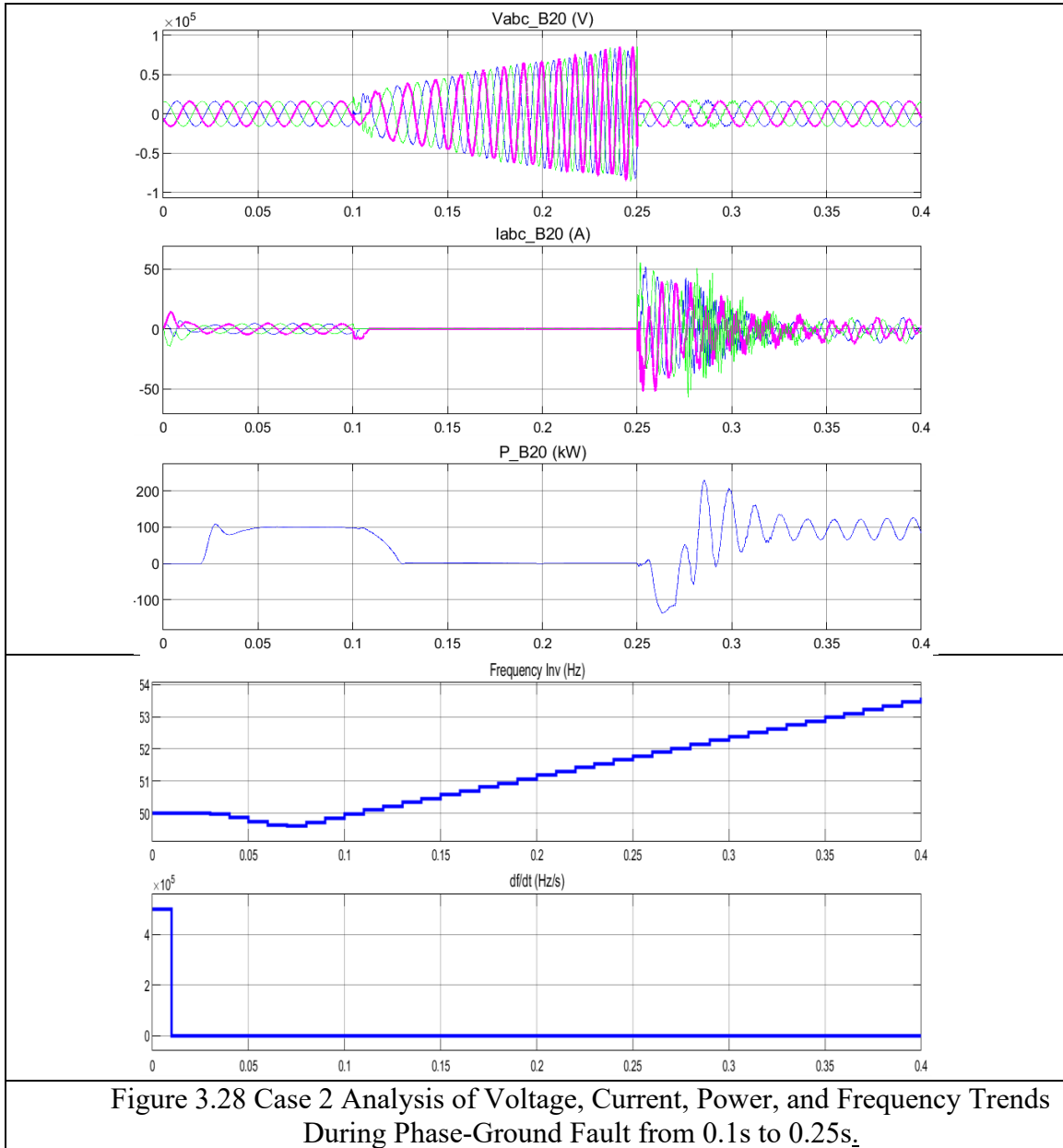
Figure 3.25 Case 1 Analysis of Voltage, Current, Power, and Frequency Trends During Three Phase Fault from 0.1s to 0.25s.

F. Fault type: Three-Phase -ground (Fault time: 0.1s to 0.25s)

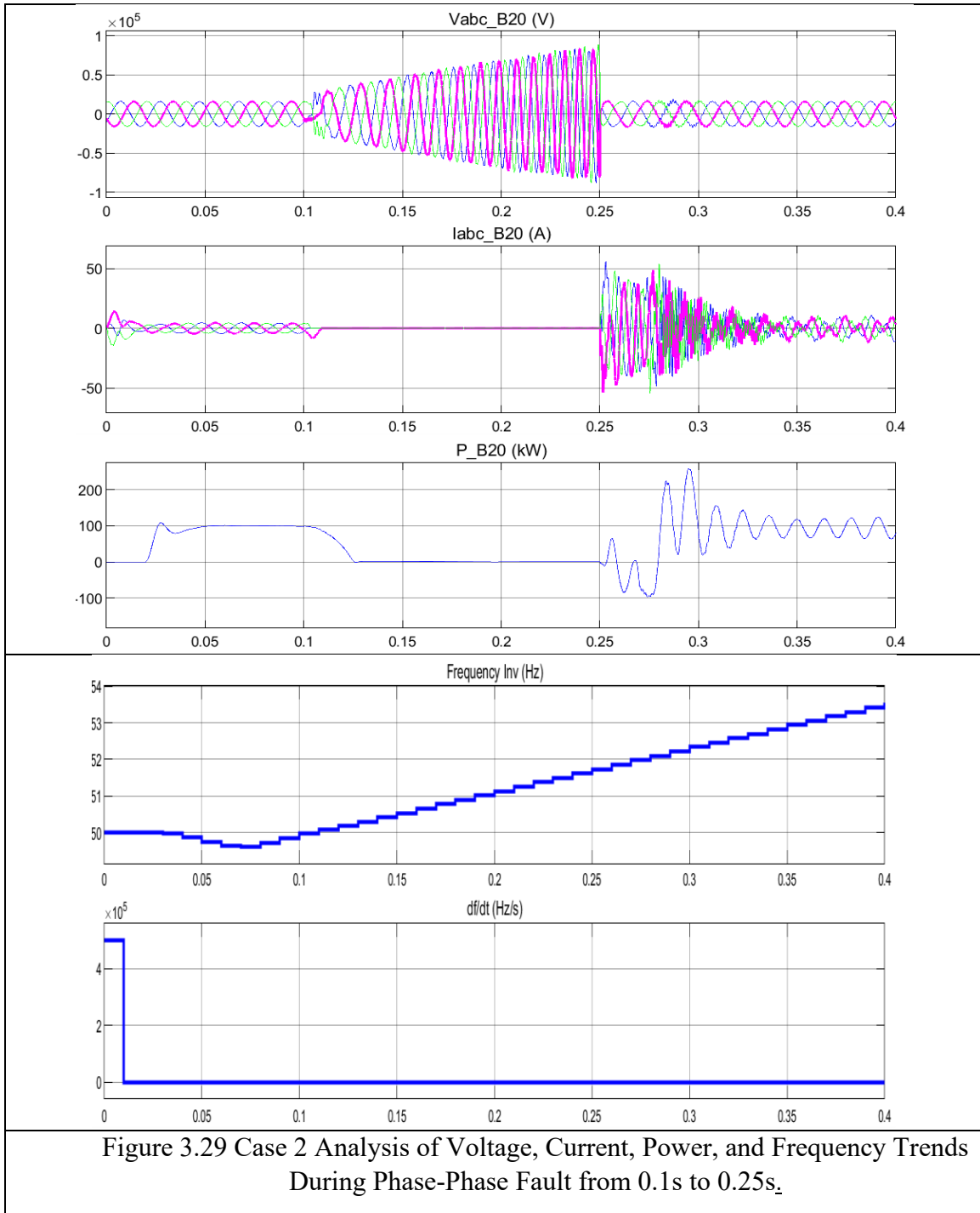


Case 2: Here, both CB1 and CB2 are in the 'on' position, implying a fully connected system with the external grid. This case is ideal for studying the system's behavior under normal operating conditions, including how it responds to faults when the full support of the grid is available.

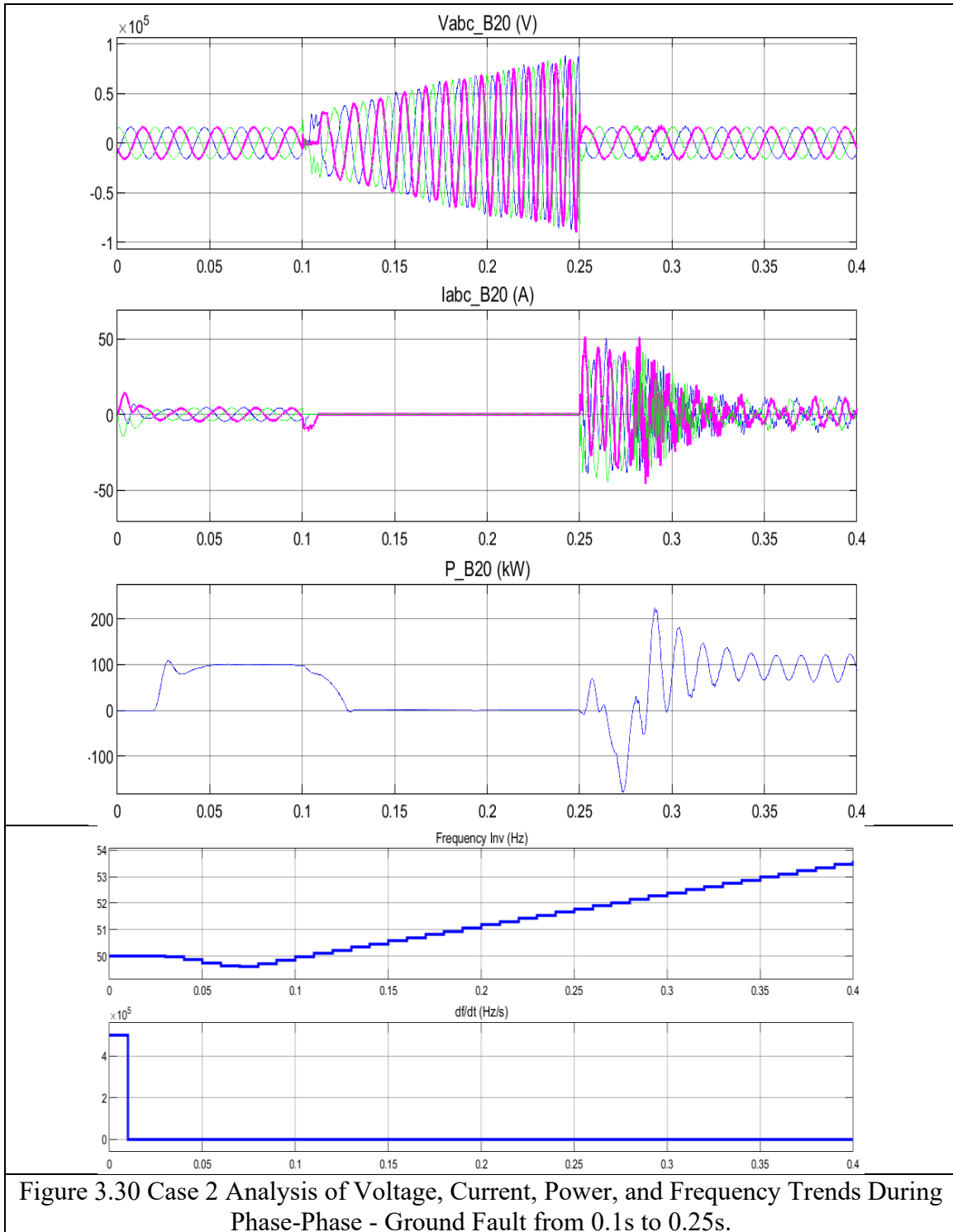
A. Fault type: phase-ground Fault time: (0.1s to 0.25s)



B. Fault type: phase-phase Fault time: (0.1s to 0.25s)



C. Fault type: phase-phase - ground (Fault time: 0.1s to 0.25s)



D. Fault type: Three-Phase Fault time: (0.1s to 0.25s)

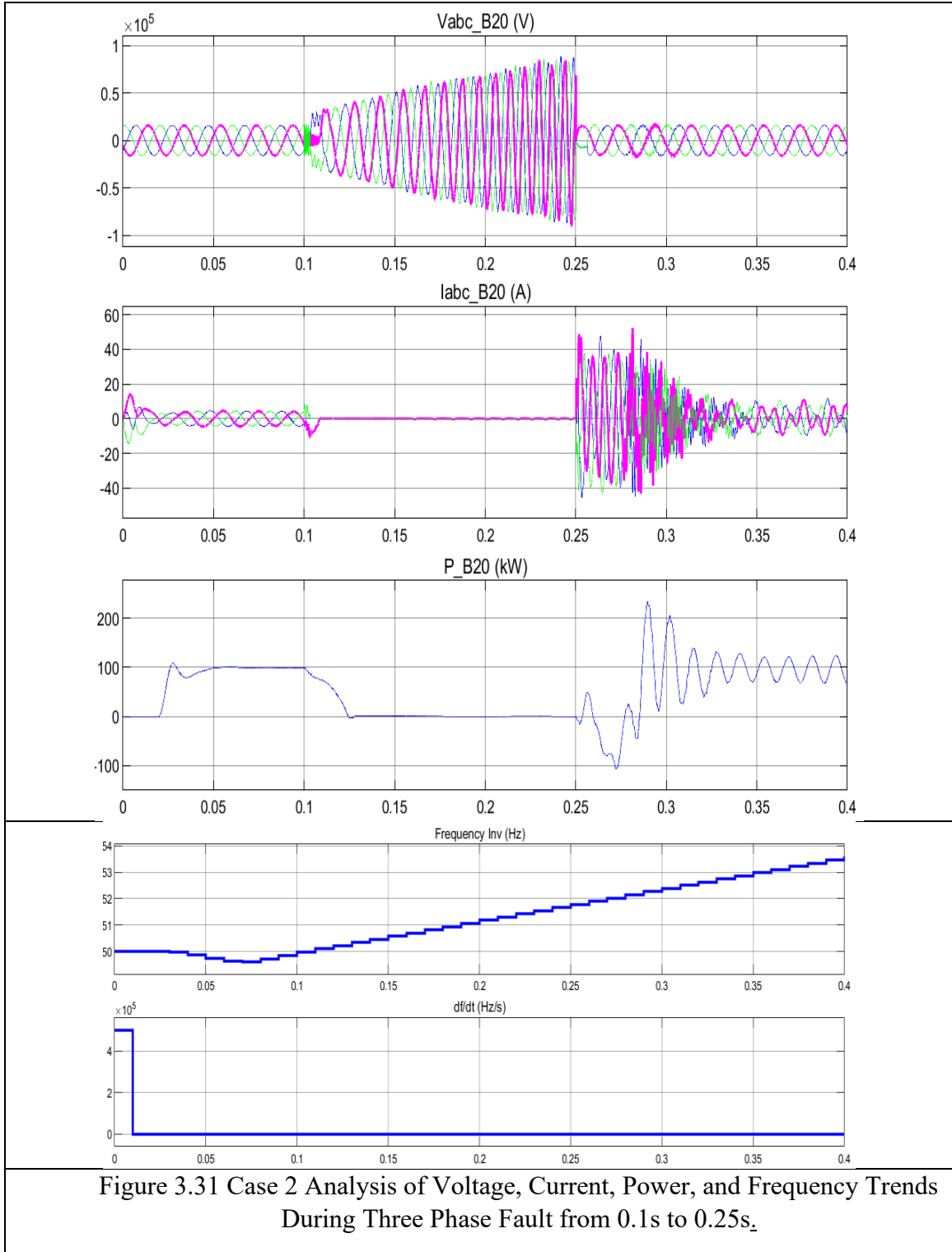
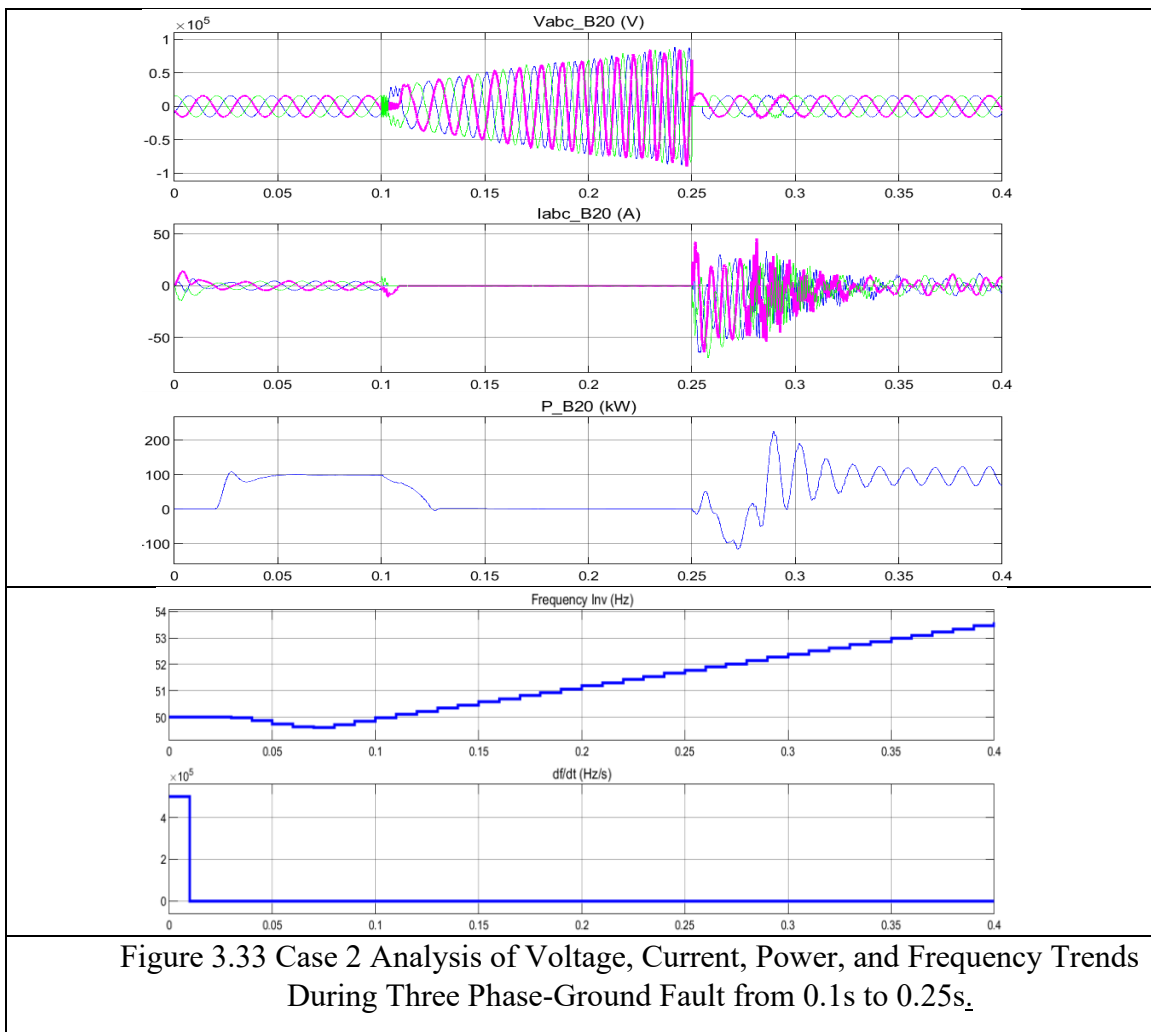
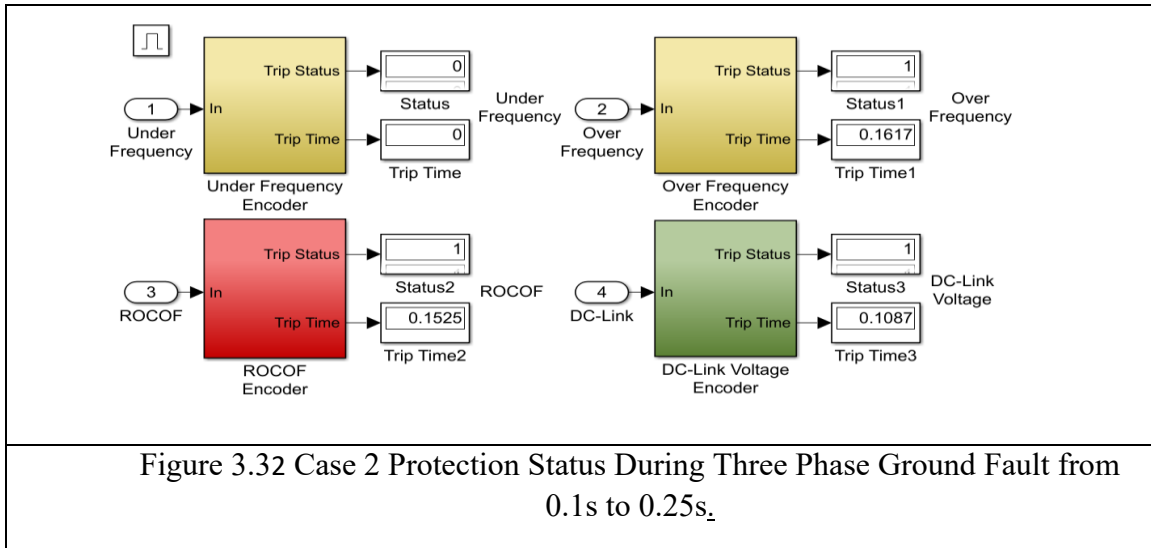


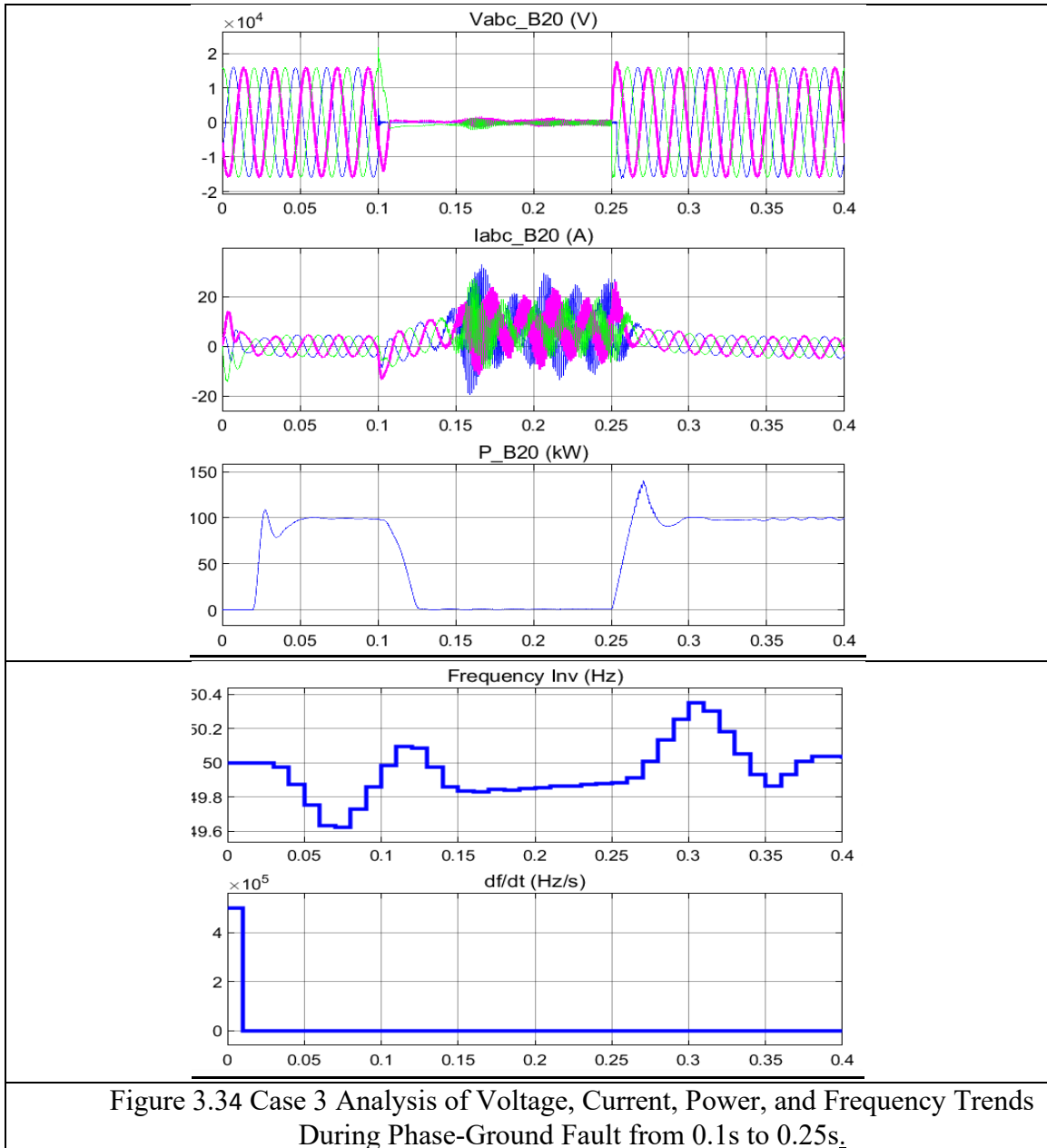
Figure 3.31 Case 2 Analysis of Voltage, Current, Power, and Frequency Trends During Three Phase Fault from 0.1s to 0.25s.

F. Fault type: Three-Phase -ground Fault time: (0.1s to 0.25s)

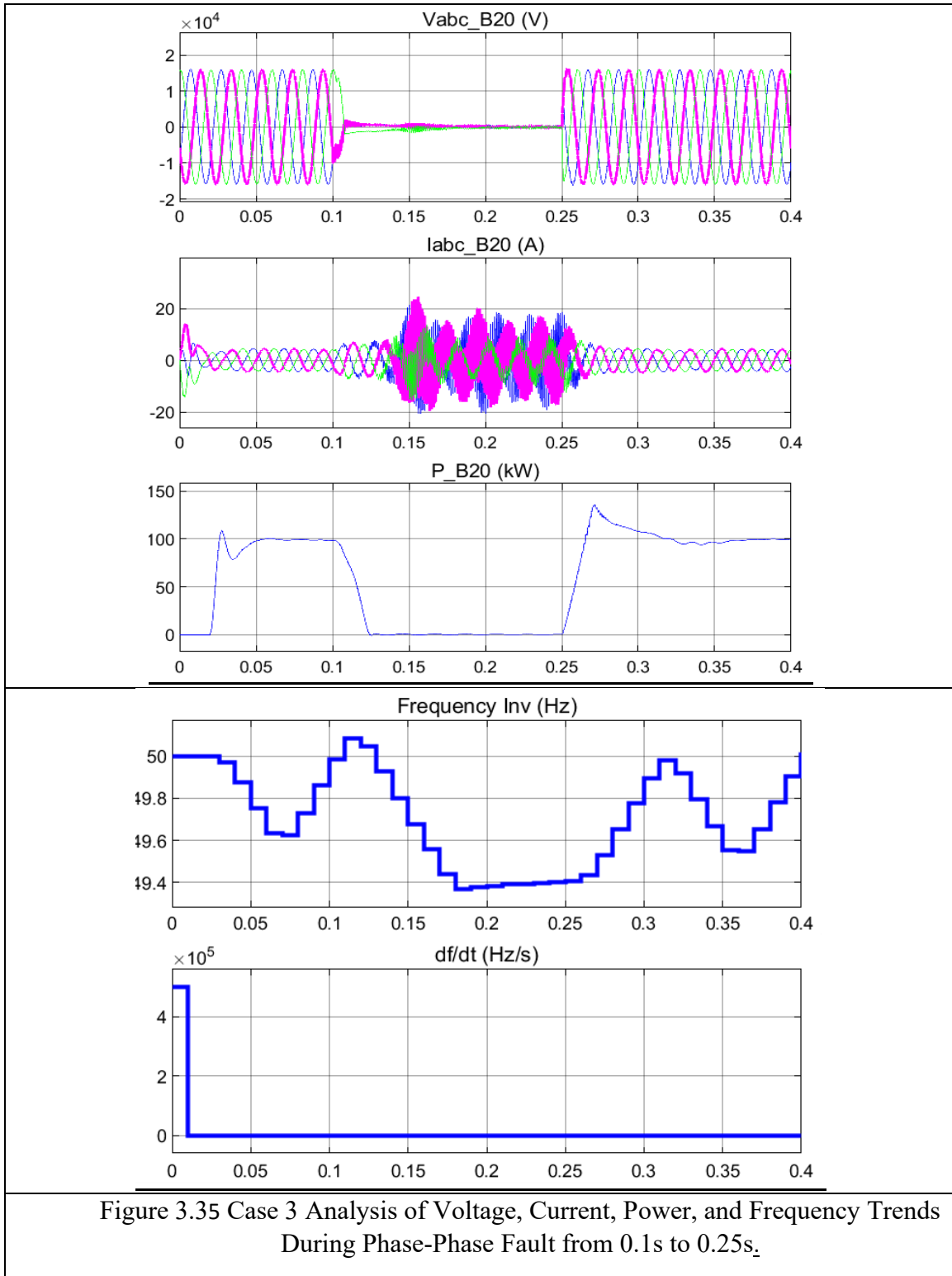


Case 3: This scenario presents a hybrid condition where CB1 is off and CB2 is on. This partial connection to the grid can provide insights into how the system behaves under partial grid support, which is a valuable scenario for understanding the dynamics of grid support during fault conditions and partial islanding situations.

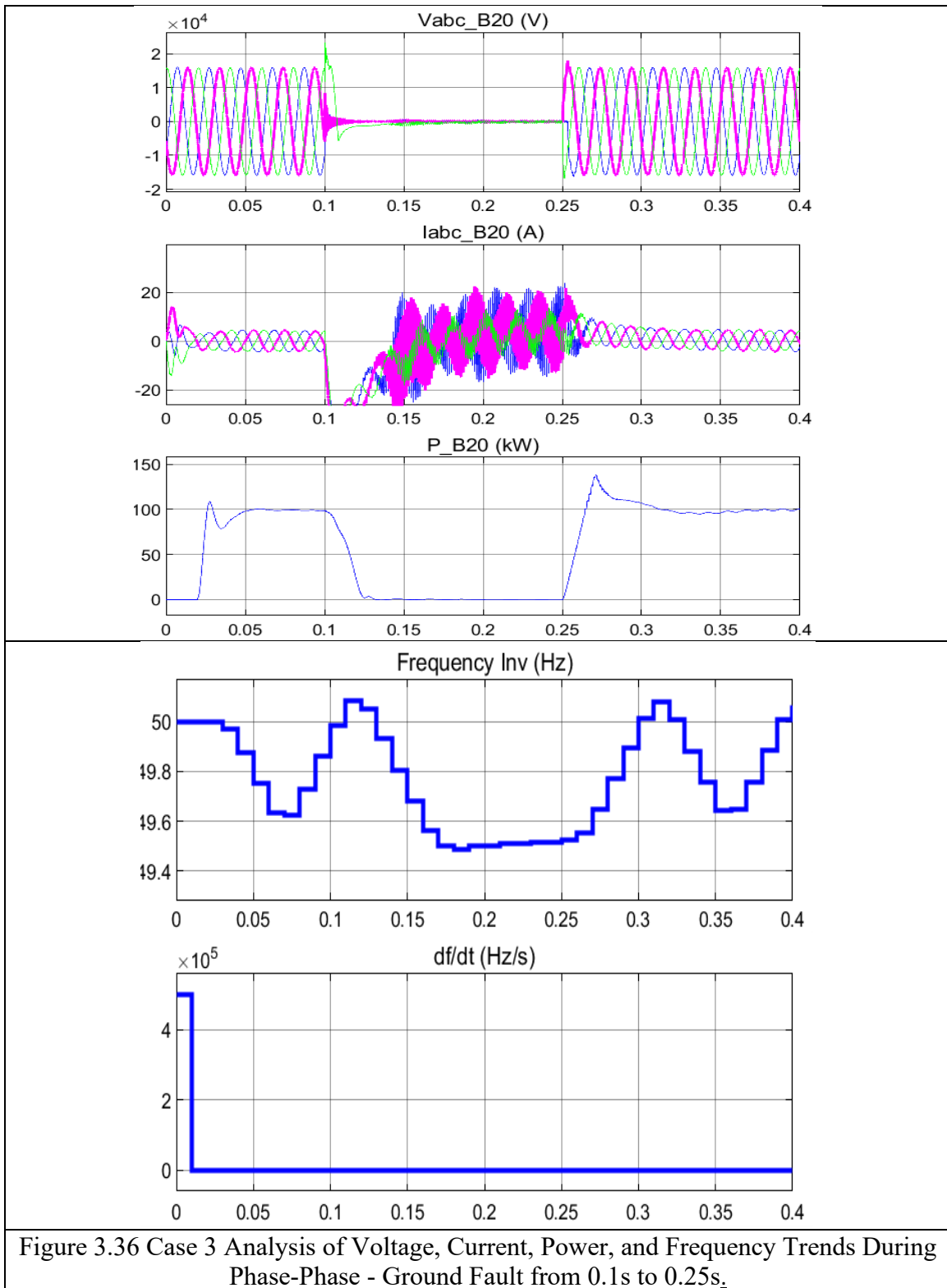
A. Fault type: phase-ground Fault time: (0.1s to 0.25s)



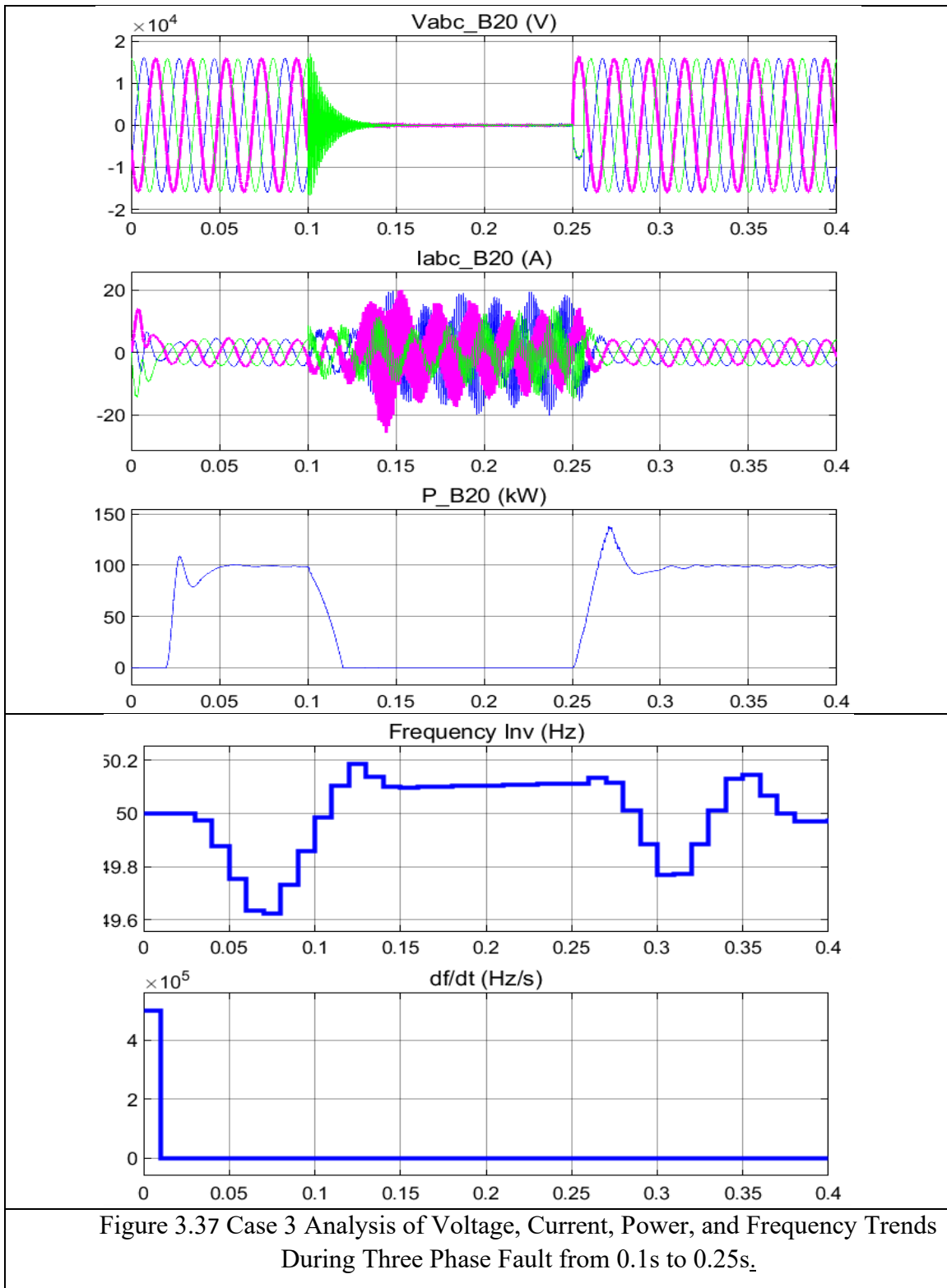
B. Fault type: phase-phase Fault time: (0.1s to 0.25s)



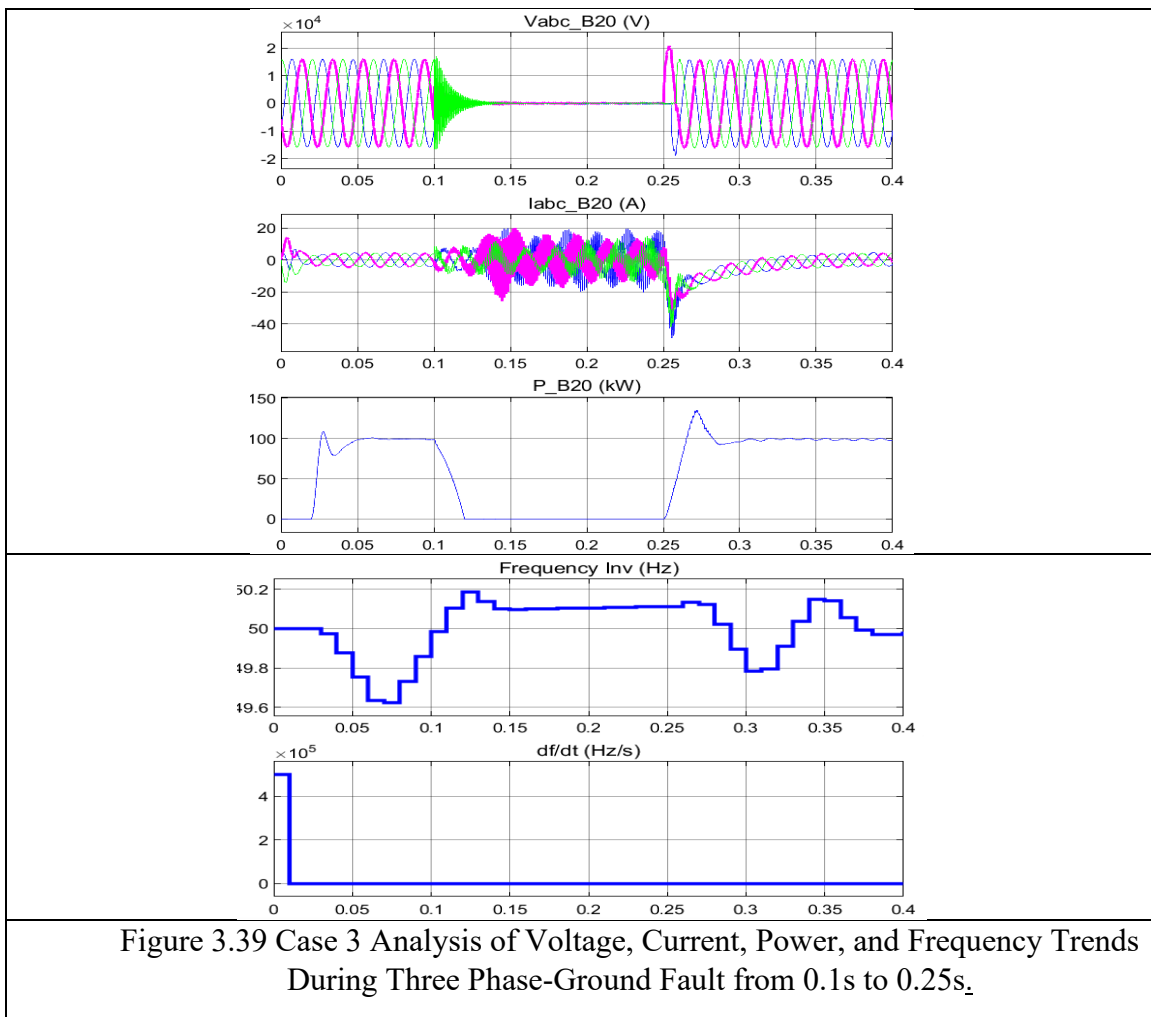
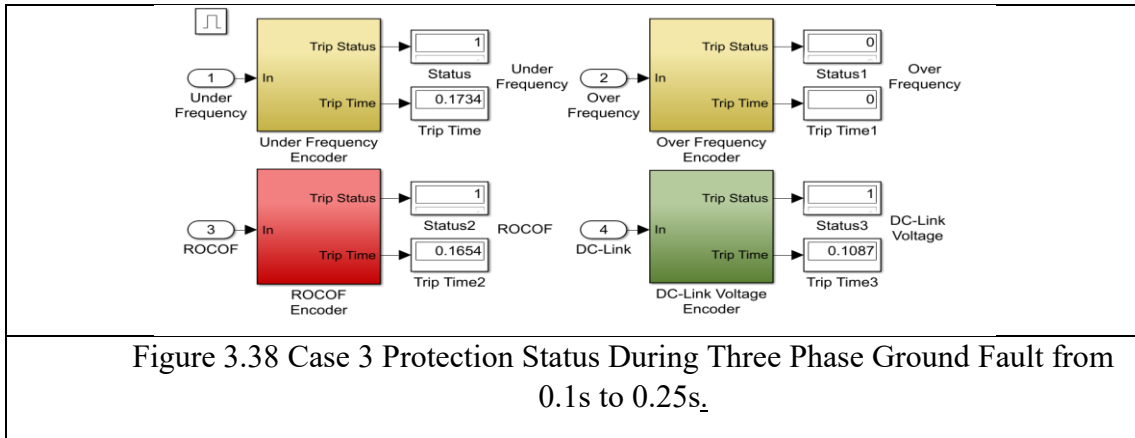
C. Fault type: phase-phase -ground Fault time: 0.1s to 0.25s



D. Fault type: Three-Phase Fault time: 0.1s to 0.25s



F. Fault type: Three-Phase -ground Fault time: (0.1s to 0.25s)



Each of these cases offers a unique perspective on the power system's behavior and the effectiveness of its protection mechanisms under different grid connection scenarios. Simulating these cases can provide valuable data for enhancing system reliability and designing robust protection schemes.

3.6 Grid disturbance

The electrical grid, a complex network of power generation, transmission lines, and distribution systems, serves as the backbone of modern society, providing electricity to homes, businesses, and industries around the world. However, this vital infrastructure is susceptible to various forms of electrical disturbances, which can disrupt its smooth operation and compromise the reliability of power supply. These disturbances come in several forms (Albadi,2015), including voltage sags and swells, voltage harmonics, spikes and surges, and transient disturbances, each with its own set of causes and consequences. Voltage sags and swells, caused by sudden changes in load demand or faults in the grid, can lead to equipment malfunctions, decreased efficiency, and potential safety hazards. Voltage harmonics, generated by nonlinear loads such as electronic devices, can distort the sinusoidal waveform of the voltage, resulting in overheating of equipment and interference with sensitive electronic devices. Voltage spikes and surges, often caused by lightning strikes or switching operations, can cause immediate damage to equipment and pose a risk of electrical fires. Transient disturbances, characterized by short-duration fluctuations in voltage or current, can disrupt the operation of equipment and cause data loss in sensitive electronic systems. The effects of these disturbances are far-reaching, impacting not only the reliability of electricity supply but also the economy, environment, and public safety. Businesses and industries may incur

significant costs due to equipment damage, downtime, and lost productivity, while energy wastage and increased carbon emissions from backup power sources contribute to environmental degradation. Detecting and monitoring electrical disturbances are essential for preventing damage and mitigating their impacts. Various techniques, such as power quality monitoring devices and remote monitoring systems, enable real-time monitoring of grid conditions and early detection of disturbances. Mitigation strategies, including surge protection devices, voltage regulators, harmonic filters, and uninterruptible power supplies (UPS), can help protect equipment and ensure the stability of the grid. However, addressing the challenges posed by electrical disturbances requires a concerted effort from stakeholders across the industry. Continued research and investment in grid resilience, along with the adoption of emerging technologies such as smart grid systems and advanced power electronics, are essential for ensuring the reliability and sustainability of the electrical grid in the face of evolving threats and demands. By understanding the causes and consequences of electrical disturbances and implementing effective mitigation measures, we can enhance the resilience of the grid and ensure a reliable supply of electricity for generations to come.

Power system apparatus performance can be significantly affected by current asymmetry, voltage asymmetry, or a combination of both. In general, generating and transmission equipment are primarily affected by current asymmetry, while customer's equipment is more susceptible to voltage unbalance. Voltage unbalance arises from two main sources: the structural asymmetry of parameters within generators, transformers, transmission, and distribution lines, and voltage drops across the system impedance due to current unbalance. The primary cause of current unbalance is loading

imbalance, which can stem from three main factors: the uneven distribution of single-phase loads, the presence of large single-phase loads, and faults within the system. In some cases, permanent current asymmetry persists during normal operating conditions, as observed in residential and commercial single-phase loading, traction systems, and arc furnaces. Current asymmetry may also occur during transient conditions, such as faults, where temporary current asymmetry is induced. Examples of such transient unbalanced conditions include single-line-to-ground faults, line-to-line faults, and double-line-to-ground faults. While unbalanced faults represent extreme instances of current unbalance, they typically last only for a few seconds. However, if not promptly cleared, these conditions have the potential to escalate into system instability, highlighting the critical importance of timely fault detection and mitigation measures within the electrical grid.

Indeed, the suite of protection measures encompassing Voltage amplitude in per unit (V_{pu}), Rate of change of voltage (dV/dt), Voltage total harmonic distortion ($THDV$), Current total harmonic distortion ($THDI$), Frequency in Hertz (f), Rate of change of frequency (df/dt), Rate of change of power (dP/dt), Rate of change of reactive power (dQ/dt), Voltage negative sequence distortion ($NegSV/dt$), and Current negative sequence distortion ($NegSI/dt$) play crucial roles in detecting and mitigating disturbances within the electrical grid. These protections serve as the frontline defense against various types of disruptions, offering insights into the grid's health and stability. Typically, certain disturbances manifest concurrently, revealing the interconnected nature of grid vulnerabilities. For instance, voltage amplitude fluctuations might coincide with frequency deviations, indicating a potential imbalance between generation and load. Similarly, harmonic distortions in

voltage and current waveforms often occur in tandem, signifying nonlinear loads or faulty equipment. Additionally, rapid changes in voltage or frequency (dV/dt , df/dt) may trigger protective measures to prevent equipment damage or grid instability. Moreover, the rate of change of power and reactive power (dP/dt , dQ/dt) serves as early indicators of system stress, prompting corrective actions to maintain operational reliability. Furthermore, negative sequence distortions in voltage and current waveforms can signal asymmetrical faults or unbalanced load conditions, necessitating swift intervention to prevent cascading failures. By monitoring and analyzing these parameters in real-time, grid operators can swiftly identify, isolate, and mitigate disturbances, ensuring the continued reliability and resilience of the electrical grid.

Therefore, as the complexity of electrical power systems continues to grow and the demand for electricity escalates, the importance of developing a reliable, efficient, and secure power supply becomes paramount. The integration of smart grid technologies offers a promising solution to address these challenges, particularly in mitigating grid disturbances. The Smart Grid (SG) represents the next generation of power systems, characterized by its fault identification and self-healing capabilities. By leveraging bi-directional flows of electricity and information, the SG enhances system resilience and operational efficiency, effectively detecting and mitigating grid disturbances in real-time. Moreover, with the increasing integration of renewable energy sources and the active participation of consumers in demand response programs (Albadi,2020), the SG enables greater sustainability and flexibility in grid operations. Concepts such as virtual power plants (VPPs) and active demand management further enhance the adaptability and responsiveness of

the grid to changing conditions. Additionally, the monitoring and control capabilities of the SG empower both energy providers and consumers to optimize energy usage and improve overall system efficiency. With the global energy demand projected to rise substantially in the coming decades, the development and deployment of smart grid technologies are crucial for meeting the challenges of the future energy landscape. Through ongoing research and innovation, smart grids offer a pathway towards a more resilient, sustainable, and efficient energy infrastructure, ultimately ensuring the reliable delivery of electricity while effectively managing grid disturbances.

3.7 Enhanced Performance Management through the Use of a Dynamic Model for Islanding Detection

The implementation of the Dynamic Islanding Detection Model marks a significant advancement in the realm of power system management, offering a paradigm shift from conventional methods. This innovative approach primarily enhances the reliability and efficiency of power grids by swiftly and accurately identifying islanded sections, which are parts of the grid isolated due to disruptions like faults or maintenance activities. Unlike static models, the dynamic model adapts to real-time changes in the grid, leveraging advanced algorithms and data analytics. This adaptability not only ensures a faster response to power inconsistencies but also minimizes the risk of equipment damage and power outages, thereby maintaining a stable and continuous power supply. Furthermore, this model enhances operational efficiency by reducing the need for manual monitoring and intervention, allowing for more effective resource allocation and decision-making. The transition to the Dynamic Islanding Detection Model thus represents a forward-thinking approach in power system management, embracing

technological innovation for improved safety, reliability, and operational efficiency.

Utilizing dynamic power system models, as opposed to traditional static models, presents substantial advantages in the realms of power system analysis, planning, and operation, crucial for adapting to the complexities of modern electrical grids.

These models are essential for improved stability analysis, enabling a detailed assessment of the system's response to disturbances like faults, rapid load changes, or generator outages, which is critical in predicting and mitigating potential issues such as voltage instability, frequency deviations, and cascading failures. They are particularly significant for integrating renewable energy sources like wind and solar power. As these sources are intermittent and variable, dynamic models help in understanding and managing their impact on grid stability and reliability, thereby supporting a sustainable energy transition without compromising grid performance. Additionally, these models are pivotal in optimizing grid operation and control, allowing operators to simulate various scenarios like peak load conditions, maintenance schedules, and emergency situations for more effective grid management, including improved load forecasting, demand response strategies, and contingency planning.

Moreover, dynamic power system models facilitate the implementation of advanced technologies, including smart grids, demand-side management, and energy storage systems, by illuminating the complex interactions between these technologies and the power system. This is vital for designing strategies that maximize the benefits of these technologies while maintaining grid integrity. These models are often required for regulatory compliance and are

instrumental in long-term system planning and investment decisions, ensuring that power systems can meet future demands reliably and efficiently. Furthermore, by accurately predicting system behavior, dynamic models enable cost-effective maintenance and infrastructure upgrades, focusing investments where most needed and reducing unnecessary expenditures. In summary, transitioning to dynamic power system models is crucial for modern power systems, offering enhanced accuracy, stability, integration of renewable resources, optimized operation, facilitation of advanced technologies, regulatory compliance, and cost-effective maintenance strategies, thereby ensuring a stable, efficient, and sustainable power system.

3.8 Summary

The research utilizes a comprehensive model developed by Ioan Viorel Banu and Marcel Istrate, as a foundational framework for studying solar power conversion and distribution dynamics within power grids. This model, which connects a 100kW Photovoltaic (PV) Array to a 20kV utility grid operating at 50Hz, incorporates high-frequency power electronic converters and a sophisticated control system to efficiently transform solar energy into grid-compatible power. The study also addresses the challenges posed by islanding, where a portion of the grid remains powered despite disconnection from the main source. To mitigate risks, advanced protection mechanisms, tailored for detecting anomalies associated with islanding and other grid disturbances, have been developed. International standards guide the development of these mechanisms, setting requirements for detection speed, frequency range, and nominal voltage values.

The implementation of protection mechanisms in MATLAB/Simulink enables detailed simulation and analysis under various scenarios, aiding in the

development of machine learning models. These models leverage simulation data to predict, detect, and optimize protection system responses, enhancing grid stability and reliability.

The research further explores various grid disturbances, such as voltage sags, harmonics, spikes, and transients, emphasizing their impact on grid operation and reliability. The Dynamic Islanding Detection Model represents a significant advancement, offering real-time adaptability and enhancing operational efficiency by swiftly identifying islanded sections and minimizing equipment damage and power outages.

Dynamic power system models offer substantial advantages over static models in analyzing, planning, and operating modern electrical grids. They enable improved stability analysis, facilitate renewable energy source integration, and optimize grid operation and control, supporting a sustainable energy transition while maintaining grid performance and reliability.

Chapter 4

Developing Customized Dataset

Chapter 4 Developing Customized Dataset

4.1 Introduction

From raw data, it can be extracted features that represent the real data. These features are used to train and test the algorithm to generate a learned model. This learned model is then utilized to get the outcome of any new inputs given to the model. So, it is required to analyze the data by training and testing with more appropriately labeled data for any supervised machine learning technique.

4.2 Data augmentation techniques

The data augmentation techniques are used to improve the use of available data and avoid the overfitting issue of the data. For any limited data problem, the augmentation techniques will act as data-space solution which also improves the attributes and size of training datasets. The main solution techniques are as follow:

- 1- Flipping: Flipping has been considered as valuable on datasets like ImageNet and CIFAR-10 and it is very simple to implement.
- 2- Color space: Separating the particular colors into the three colors Red, Green, or Blue is a very simple technique and it is used in recognizing the image. There are three dimensions used in digital image data which are height, width, and color channels. In addition, straightforward matrix operations can be used to increase or decreasing the image brightness.
- 3- Cropping: Cropping is used as a specific image processing step to produce an effect similar to translate through random cropping

- 4- Rotation: The rotation augmentations can be obtained by rotation the image for the degrees between 0 to 360 degrees however the small rotations (from 0 to 20 degrees) are more useful.
- 5- Translation: It is required to shift the image in all directions (up, down, left or right) to avoid positional bias within the image data.
- 6- Noise injection: to improve the CNN, it is required to inject noise within images to get more robust features.

4.3 Imbalanced data

Unfortunately, negative samples represent more than positive samples, so biological data tend to be unbalanced which leads to undesirable results. To solve this issue, it is required to employ the correct criteria for evaluating and constructing models for every hierarchical level and compare those models to segregate the data.

4.4 Dataset for islanding detection

It is required to design CNN for islanding detection based on actual dataset by using several parameters at the point of common coupling. The parameters that will be used in the design are voltage, frequency, power, harmonic and negative sequence.

The first step will concentrate on designing the architecture of the CNN which means specifying the number of layers and the filter required for optimum islanding performance. After completing the designing of the architecture then the classification of the data will be the second step before the trained the model.

4.5 SIMULINK Model to Generate Dataset for Islanding Detection

Islanding detection techniques are dependent on network fault and connection type of the distributed generation to the network system. A major challenge is to design an (islanding model technique) to detect islanding very accurately and in an optimized time consumption manner for different distributed generation scheme types and for multiple units connecting together in power network-grid. A Simulink model of a 100 kW array connected to a 25-kV grid via a DC-DC boost converter and three phase three level voltage source converters (VSC). Maximum power point tracking (MPPT) technique is implemented to control DC-DC boost converter based on the Perturb and observe technique. The control of three phase three level inverter is depend on pulse width modulation (PWM) and Proportional Integral (PI) controllers.

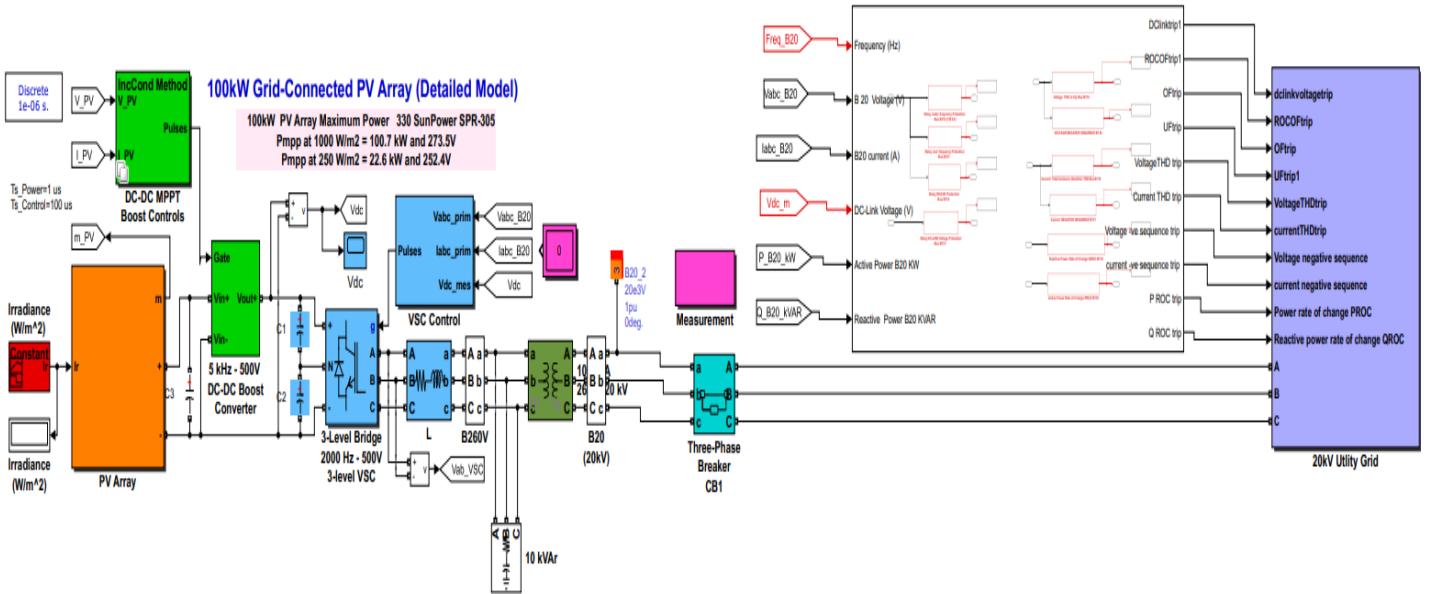


Figure 4.1 Simulink model with 10 protections implemented.

The power system represented by ten plants each one is protected via one electronic relay as following:

A. Under/Over frequency Protection:

Under/Over frequency protection is a crucial aspect of islanding detection in power systems. This method operates on the principle that when a portion of the grid becomes "islanded," or disconnected from the main power supply, there is a significant deviation in the frequency of the electrical system within the islanded section. To detect this, under/over frequency protection involves setting thresholds: an under-frequency threshold and an over-frequency threshold. Typically, these thresholds are set slightly below and above the standard operating frequency (usually 50 Hz or 60 Hz, depending on the region). If the frequency falls below or rises above these set limits, it indicates a potential islanding situation, prompting protective measures to disconnect the islanded section to prevent damage to the system and ensure safety. This method is widely used due to its effectiveness and simplicity in detecting islanding conditions. The system's frequency should be kept at 50 Hz. Relay trip in frequency goes under 49.5 Hz or above 50.5 Hz.

B. ROCOF Protection:

The Rate of Change of Frequency (RoCoF) protection is an integral part of islanding detection in power systems. It focuses on monitoring the rate at which the system frequency changes over time, rather than just the frequency value itself. In an islanding event, the disconnection of a part of the grid from the main supply can lead to rapid changes in frequency within the isolated section. RoCoF protection systems are set up with specific thresholds for the rate of frequency change, typically expressed in Hz/s (hertz per second). If the

rate at which the frequency changes exceed this predefined threshold, it signals a potential islanding situation. This method is particularly effective in detecting islanding quickly and is often used in conjunction with under/over frequency protection. The RoCoF threshold is carefully set to avoid false tripping due to normal load variations, yet sensitive enough to act promptly during actual islanding scenarios. This approach enhances the overall reliability and safety of the power system. The System rate of change of frequency ROCOF should not exceed 12 Hz/s. If ROCOF exceeds 12 Hz/s the relay should trip to isolate fault.

C. Over Voltage protection:

Over Voltage Protection plays a pivotal role in islanding detection in electrical power systems. This strategy is designed to monitor and respond to excessive voltage levels within a part of the power grid. In the context of islanding, when a segment of the grid becomes isolated from the main supply, there can be a significant rise in the voltage within this "islanded" section, primarily due to the absence of load to absorb the generated power. Over Voltage Protection involves setting a specific voltage threshold, which is determined based on the standard operating voltage levels of the system. If the voltage in any part of the system exceeds this set threshold, it is an indication of a potential islanding condition or other system abnormalities. The threshold for over voltage protection is typically a percentage above the nominal voltage level (e.g., 110% of the nominal voltage). The protection system is designed to quickly detect and respond to these over voltage situations by triggering protective actions like isolating the affected section from the rest of the grid. This not only helps in detecting islanding scenarios but also protects the electrical equipment and ensures the safety and stability of the power system. It's crucial

that the over voltage protection is accurately calibrated to avoid unnecessary disconnections while ensuring prompt action in genuine islanding or over voltage scenarios. The System DC-LINK voltage should not exceed 550 V. If system voltage exceeds 550 V the protective relay should trip at that time to isolate fault. DC Over Voltage Protection is essential in systems where direct current (DC) is used, particularly in the context of islanding detection in distributed generation systems like solar photovoltaic (PV) arrays. This protective mechanism is designed to monitor the voltage level in the DC part of the system, ensuring that it does not exceed a predetermined threshold. In an islanding event, the disconnection of a segment of the grid can lead to a significant increase in the DC voltage, especially in systems like solar PV installations where the generation may continue even after grid separation.

The DC Over Voltage Protection system involves setting a specific threshold, usually a certain percentage above the standard operating DC voltage level. This threshold is carefully determined to balance the need for prompt islanding detection and the avoidance of unnecessary tripping due to normal fluctuations in voltage. If the DC voltage exceeds this threshold, it indicates a potential islanding situation or other abnormal conditions, such as faults in the PV system or issues with the power electronics.

Upon detecting an over voltage condition, the protection system initiates corrective actions. These actions may include disconnecting the DC source from the rest of the system, shutting down inverters, or activating other protective devices. This not only helps in detecting and mitigating islanding scenarios but also protects the system components from potential damage due to high voltage. Proper calibration and maintenance of DC Over Voltage

Protection systems are crucial for the safe and efficient operation of DC power systems, particularly in renewable energy applications.

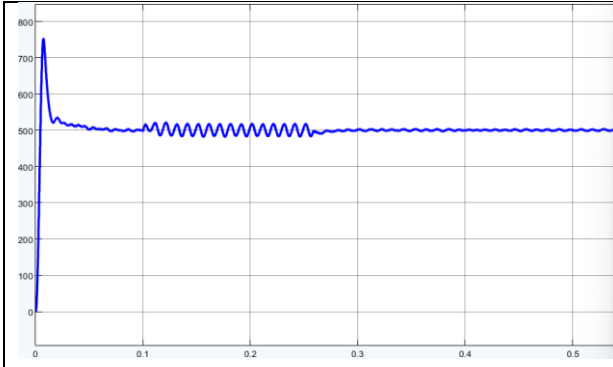


Figure 4.2 DC Link Voltage Trends During one Phase Fault from 0.1s to 0.25s.

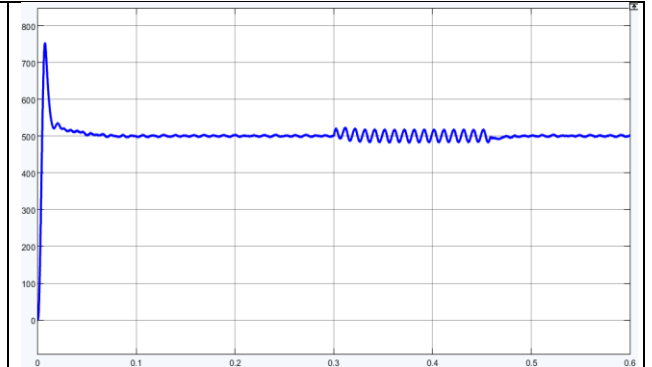


Figure 4.3 DC Link Voltage Trends During one Phase Fault from 0.3s to 0.45s.

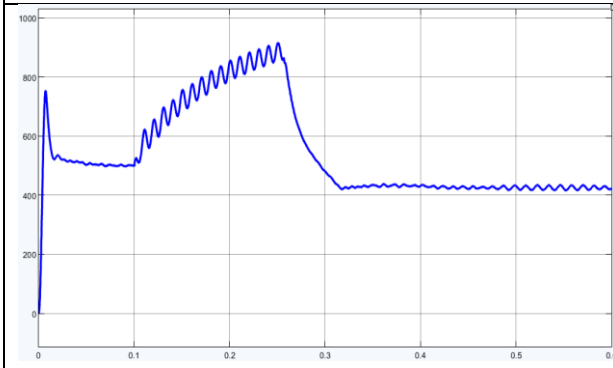


Figure 4.4 DC Link Voltage Trends During Two phase Fault from 0.1s to 0.25s.

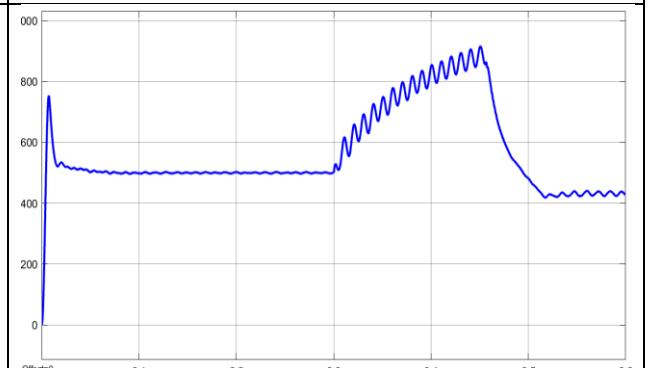


Figure 4.5 DC Link Voltage Trends During Two phase Fault from 0.3s to 0.45s.

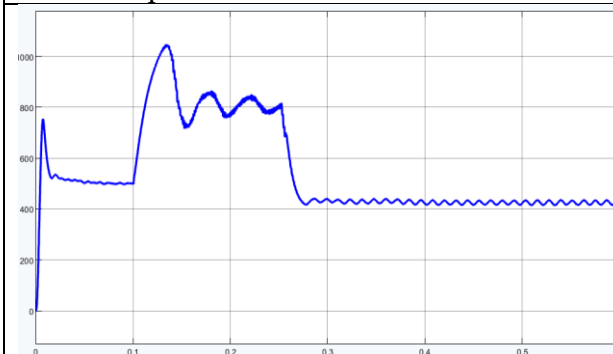


Figure 4.6 DC Link Voltage Trends During Three phase Fault from 0.1s to 0.25s.

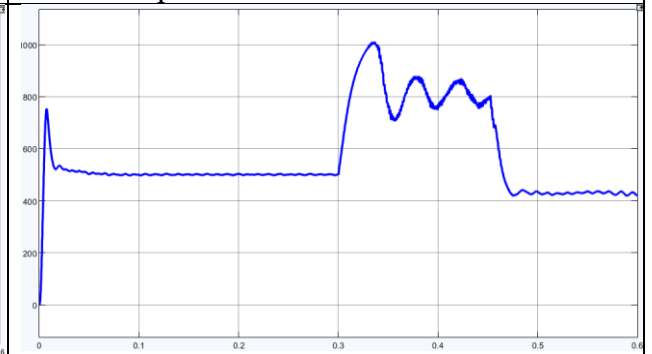


Figure 4.7 DC Link Voltage Trends During Three phase Fault from 0.3s to 0.45s.

D. Voltage rate of change Protection

Voltage Rate of Change (*VoCo*) Protection is an essential mechanism in power systems, particularly for the detection and management of islanding events and other grid anomalies. This protection strategy focuses on monitoring the rate at which voltage changes over time. Similar to Frequency Rate of Change (*RoCoF*), *VoCo* is crucial in identifying situations where the voltage changes more rapidly than normal, which can be indicative of islanding or other system disturbances. When a part of the grid becomes isolated, the voltage within this section can fluctuate significantly and rapidly, due to the imbalance between local generation and load. *VoCo* Protection involves setting specific thresholds for the acceptable rate of voltage change, typically measured in volts per second (V/s). These thresholds are carefully calibrated based on the typical operational characteristics of the grid and the specific requirements of the system. If the rate of voltage change exceeds these predefined limits, it suggests an abnormal condition, possibly islanding. The protection system then takes necessary actions, such as tripping certain circuit breakers, adjusting voltage regulation equipment, or isolating the affected section of the grid. This not only aids in promptly detecting islanding scenarios but also helps in maintaining overall voltage stability and protecting the system from potential damages caused by rapid voltage fluctuations.

Effective *VoCo* Protection requires sophisticated monitoring equipment and control systems to accurately detect and respond to these rapid changes in voltage. This ensures the reliability and safety of the power grid, particularly in systems with high levels of distributed generation, where islanding and other voltage-related issues are more prevalent. The VROC relay is configured where threshold is $(50 \frac{V}{s})$.

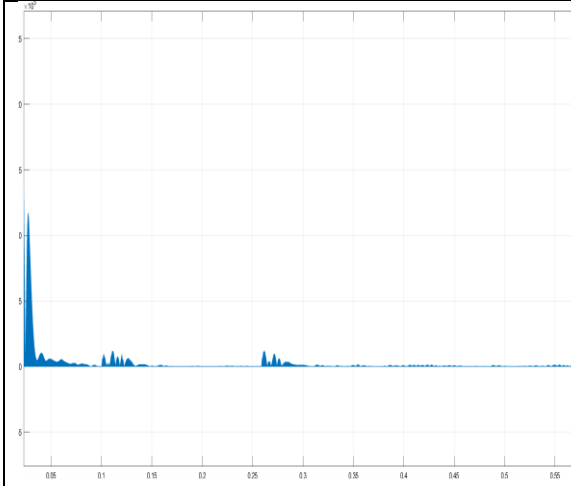


Figure 4.8 ROCOV Trends During One Phase Fault from 0.1s to 0.25s.

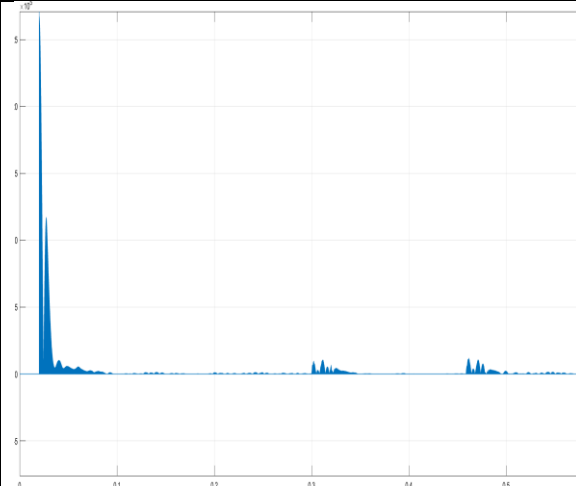


Figure 4.9 ROCOV Trends During One Phase Fault from 0.3s to 0.45s.

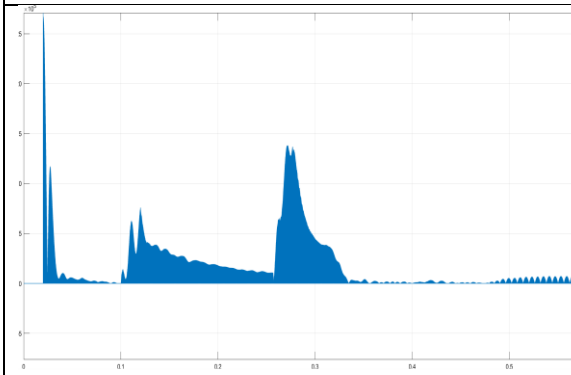


Figure 4.10 ROCOV Trends During Two Phase Fault from 0.1s to 0.25s.

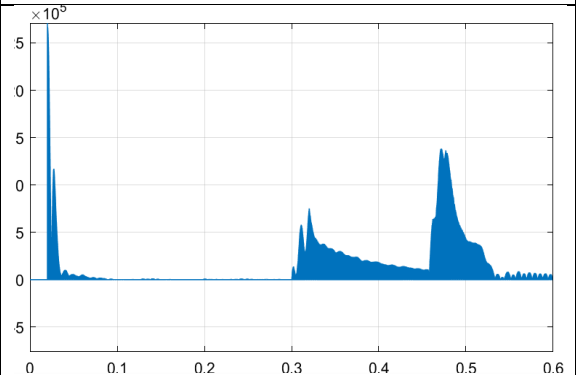


Figure 4.11 ROCOV Trends During Two Phase Fault from 0.3s to 0.45s.

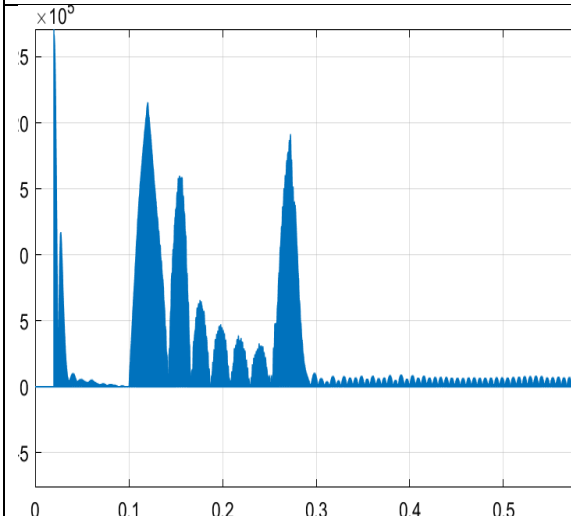


Figure 4.12 ROCOV Trends During Three Phase Fault from 0.1s to 0.25s.

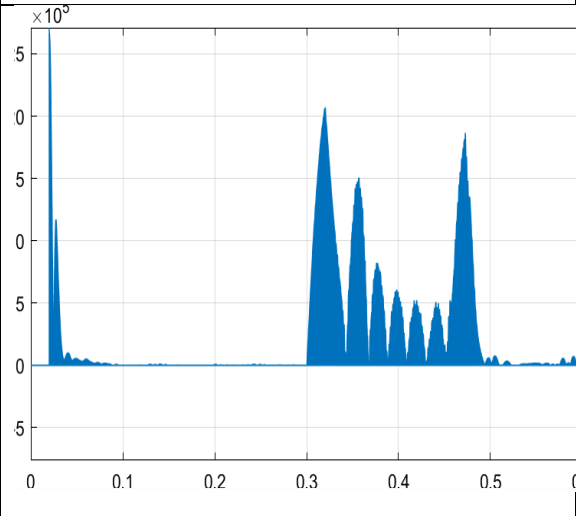


Figure 4.13 ROCOV Trends During Three Phase Fault from 0.3s to 0.45s.

Immediately after voltage rate of change magnitude exceeds 50 v/s, the relay trips at time $t=0.1002s$

E. Power rate of change Protection:

Power Rate of Change (*PoCo*) Protection is an advanced protection mechanism in power systems, particularly significant in managing grid stability and detecting islanding events. This approach focuses on monitoring the rate at which the power (either real or reactive power) changes over time within the system. Rapid changes in power levels can be indicative of various grid disturbances, including islanding.

When a part of the grid becomes isolated from the main supply, it can result in significant and rapid fluctuations in power within the islanded section, as the balance between generation and load is disrupted. *PoCo* Protection is designed to detect these rapid changes by setting thresholds for the acceptable rate of power change, usually expressed in megawatts per second (MW/s) for real.

The predetermined thresholds for *PoCo* are carefully chosen based on the normal operating conditions and the specific characteristics of the grid. These thresholds are set to be sensitive enough to detect abnormal changes indicating potential islanding or other grid issues but robust enough to avoid false triggers due to normal operational variations.

Upon detecting a power rate of change exceeding these limits, the *PoCo* Protection system initiates appropriate actions. These actions may include disconnecting the affected section from the rest of the grid, adjusting the operation of generators or other control systems, or activating other protective

devices. This not only helps in quickly identifying islanding situations but also aids in maintaining the overall power balance and stability of the grid.

The implementation of *PoCo* Protection requires sophisticated monitoring and control systems capable of accurately measuring and responding to these rapid changes in power. This protection strategy is particularly important in modern power systems with high penetration of renewable energy sources, where power levels can vary rapidly due to the intermittent nature of these sources. The Rate of Change of Power method is utilized to detect islanding events. During normal grid-connected operation, the changes in Rate of Change of Power are relatively small, whereas during islanding, they are more pronounced. However, careful consideration is needed when selecting the threshold values to effectively differentiate between switching events and islanding events. Although this method is efficient for unbalanced loads, it may fail to detect islanding in cases of balanced islanding.

A novel hybrid passive method has been proposed to identify islanding condition, which combines the changes in both the Rate of Change of Active Power (ROCOAP) and Rate of Change of Reactive Power (ROCOP) at the Point of Common Coupling (PCC).

For a three-phase system, the instantaneous active power is calculated using the equation below.

$$P_{DG} = |va||ia| \cos(\theta a) + |vb||ib| \cos(\theta b) + |vc||ic| \cos(\theta c).$$

The values va , vb , and vc represent the sampled output voltages, while ia , ib , and ic represent the sampled currents, which are measured at the output lines of the Distributed Generation (DG). By utilizing these measurements, the rate of change of active power is obtained by differentiating equations. During

grid-connected operation, the rate of change of active power remains below the predefined threshold value. However, in the event of islanding, it exceeds the threshold value. This triggers the detection of islanding and sends a signal to the breaker to disconnect the DG.

The PROC relay is configured, where threshold is 10 KW/s . Immediately after power rate of change magnitude exceeds 10 KW/s , the relay trips at time $t = 0.1002\text{s}$.

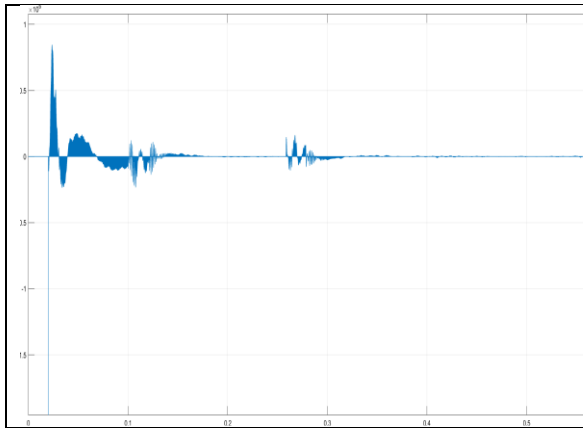


Figure 4.14 ROCOP Trends During One Phase Fault from 0.1s to 0.25s.

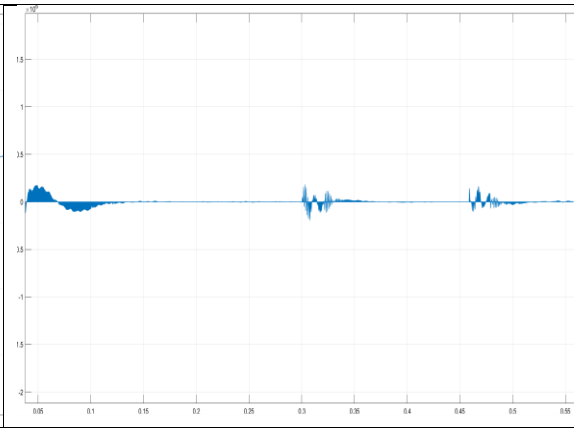


Figure 4.15 ROCOP Trends During One Phase Fault from 0.3s to 0.45s.

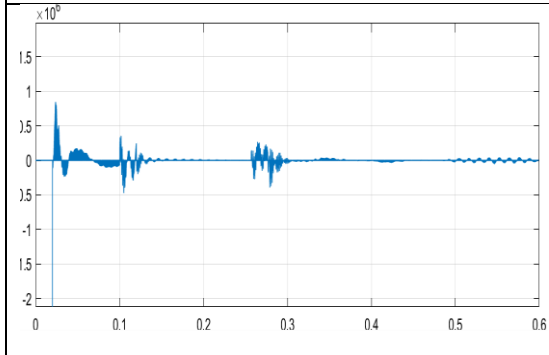


Figure 4.16 ROCOP Trends During Two Phase Fault from 0.1s to 0.25s.

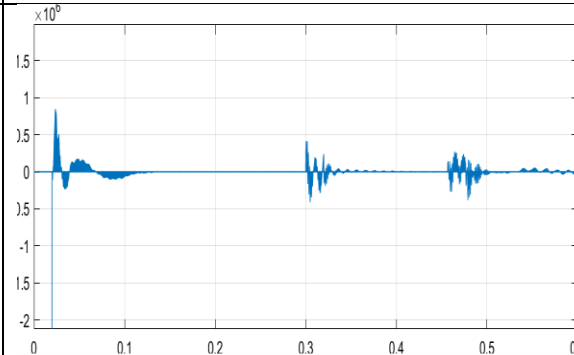


Figure 4.17 ROCOP Trends During Two Phase Fault from 0.3s to 0.45s.

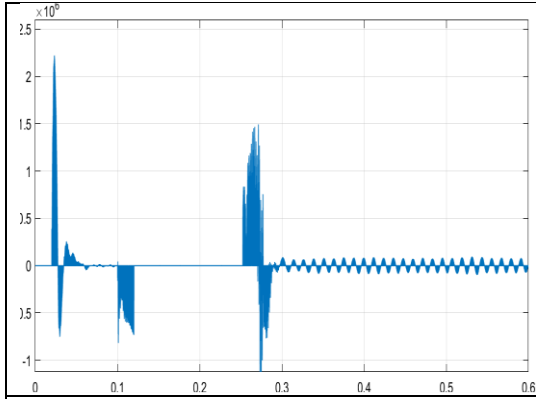


Figure 4.18 ROCOP Trends During Three Phase Fault from 0.1s to 0.25s.

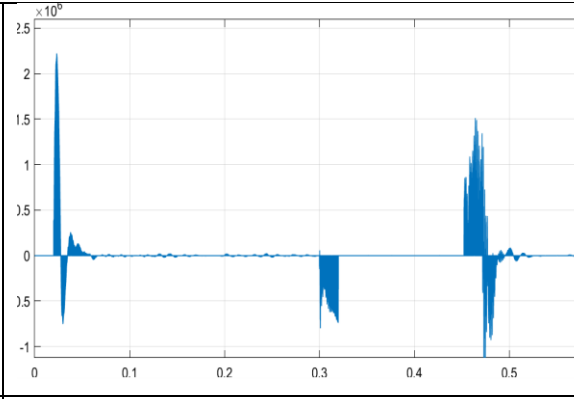


Figure 4.19 ROCOP Trends During Three Phase Fault from 0.3s to 0.45s.

F. Reactive power rate of change Protection

Reactive Power Rate of Change (*QoCo*) Protection is a specialized protection mechanism in power systems, particularly vital for maintaining grid stability and detecting islanding conditions. It focuses on monitoring the rate at which reactive power changes over time within the electrical network. Rapid changes in reactive power can signal various grid disturbances, including the occurrence of islanding events.

In an islanding scenario, when a segment of the grid becomes isolated from the main supply, there can be substantial and swift fluctuations in reactive power within this islanded section. These fluctuations are due to the sudden imbalance between local generation and load, particularly in systems with significant inductive or capacitive loads. *QoCo* Protection involves setting thresholds for the acceptable rate of reactive power change, typically measured in megavars per second (*MVar/s*).

These thresholds are determined based on the typical operational dynamics of the grid and the specific characteristics of the system, ensuring that the protection mechanism is sensitive enough to detect abnormal changes

indicative of potential islanding or other grid disturbances, yet robust enough to avoid false triggers from normal operational variations.

When the rate of reactive power change exceeds these set limits, the QoCo Protection system triggers protective actions. These may include isolating the affected grid segment, adjusting the operation of reactive power compensation devices (like capacitors or reactors), or activating other protective measures. This not only aids in quickly identifying islanding situations but also helps in managing voltage stability and power quality in the grid.

Effective implementation of *QoCo* Protection requires advanced monitoring equipment and control systems that can accurately measure and respond to rapid changes in reactive power. This type of protection is increasingly important in modern grids, especially those with high levels of renewable energy integration, where the variability of generation can lead to significant fluctuations in reactive power. The *QROC* relay is configured, where threshold is 10 KVAR/s . Immediately after power rate of change magnitude exceeds 10 KVAR/s , the relay trips at time $t = 0.1002\text{s}$.

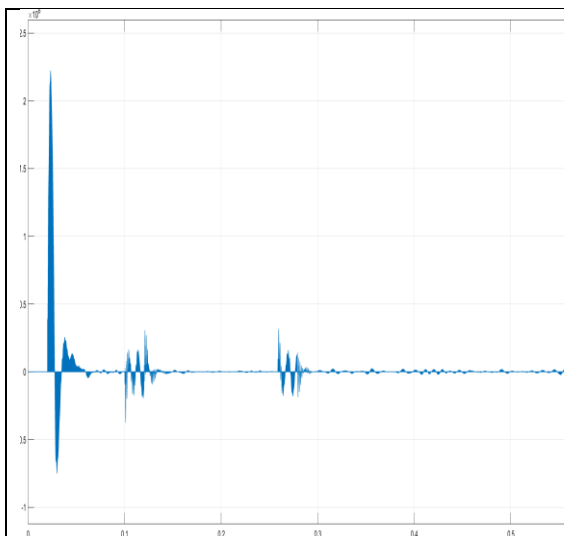


Figure 4.20 ROCOQ Trends During One Phase Fault from 0.1s to 0.25s.

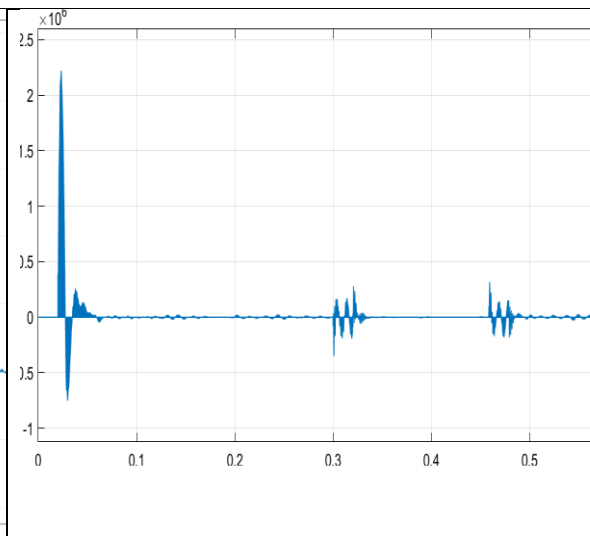
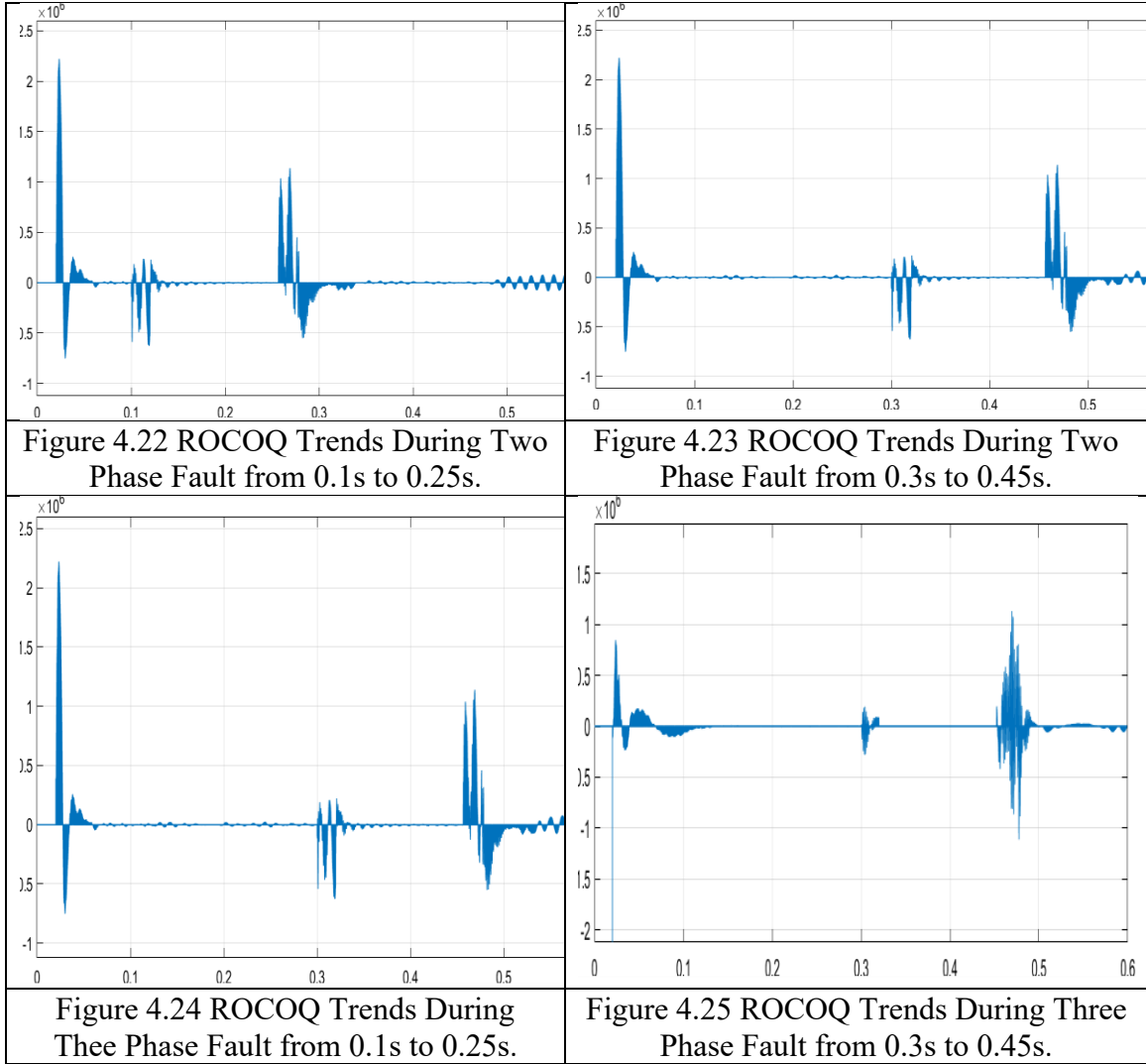


Figure 4.21 ROCOQ Trends During One Phase Fault from 0.3s to 0.45s.



G. Total harmonic voltage / dt Protection

Total Harmonic Voltage Rate of Change (THV/dt) Protection is an innovative and specialized protection mechanism in modern power systems, primarily aimed at addressing power quality issues and detecting abnormal grid conditions, including islanding. This approach focuses on monitoring the rate of change in the harmonic content of the voltage over time. Harmonics in power systems are voltage or current components at frequencies that are

multiples of the fundamental frequency (like 50 or 60 Hz), and their rapid variation can indicate various system disturbances.

In situations like islanding, where a portion of the grid gets isolated from the main supply, there can be significant and sudden changes in the harmonic profile of the voltage in the islanded section. This can occur due to the imbalance between local generation and load, and the operation of power electronic devices like inverters, which are common in distributed generation systems. THV/dt Protection involves setting thresholds for the acceptable rate of change of the total harmonic voltage, ensuring that the system can quickly respond to rapid increases in harmonic levels that may harm equipment or affect power quality.

The threshold for this protection is carefully chosen based on the typical harmonic levels in the system and the sensitivity of both the grid and connected equipment to harmonics. The aim is to have a protection system that is responsive enough to detect significant changes in harmonics, indicative of grid disturbances like islanding, while avoiding false tripping due to normal operational fluctuations.

Upon detecting an excessive rate of change in the harmonic voltage, the THV/dt Protection system initiates necessary actions, which may include isolating the affected section of the grid, adjusting the operation of filters or other harmonic mitigation devices, or implementing control changes in power electronic converters. This not only helps in identifying and mitigating islanding and other harmonic-related issues but also plays a crucial role in maintaining the overall power quality and stability of the electrical system.

Implementing THV/dt Protection requires advanced monitoring equipment capable of accurately detecting changes in the harmonic content of the voltage, as well as sophisticated control systems to effectively manage these disturbances. This protection strategy is particularly relevant in modern power systems with high penetration of non-linear loads and distributed generation sources, where harmonics can significantly impact power quality and grid stability. The Total harmonic distortion is evaluated using THD Simulink Block. If the THD of any phase voltage is above (5%). Then the corresponding generator will be disconnected from the system. Immediately after voltage harmonic THD increases to more than (5%), the relay will trip to disconnect corresponding generator.

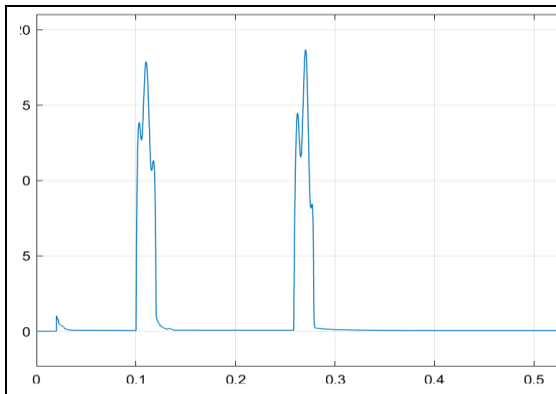


Figure 4.26 VOLTAGE THD Trends During One Phase Fault from 0.1s to 0.25s.

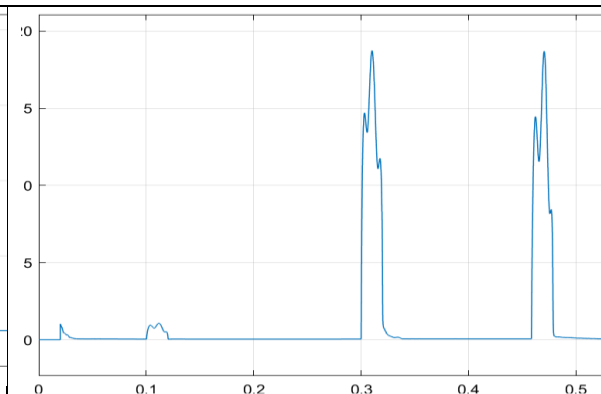


Figure 4.27 VOLTAGE THD Trends During One Phase Fault from 0.3s to 0.45s.

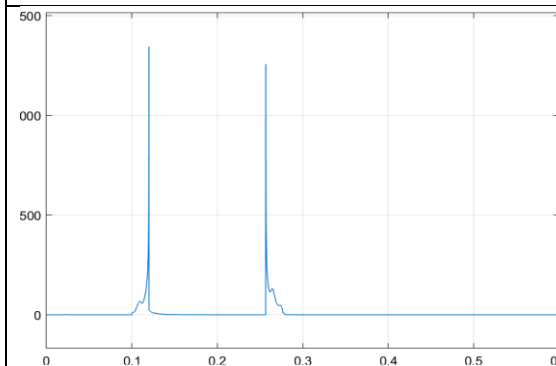


Figure 4.28 VOLTAGE THD Trends During Two Phase Fault from 0.1s to 0.25s.

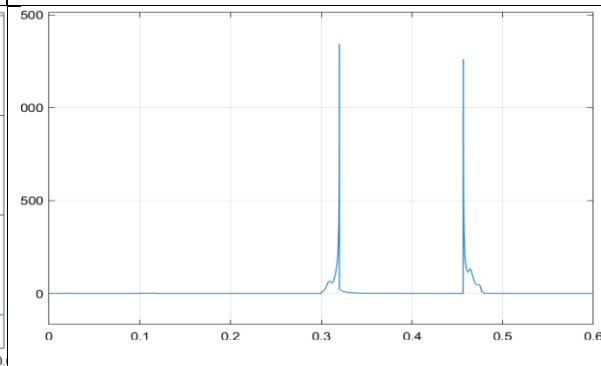
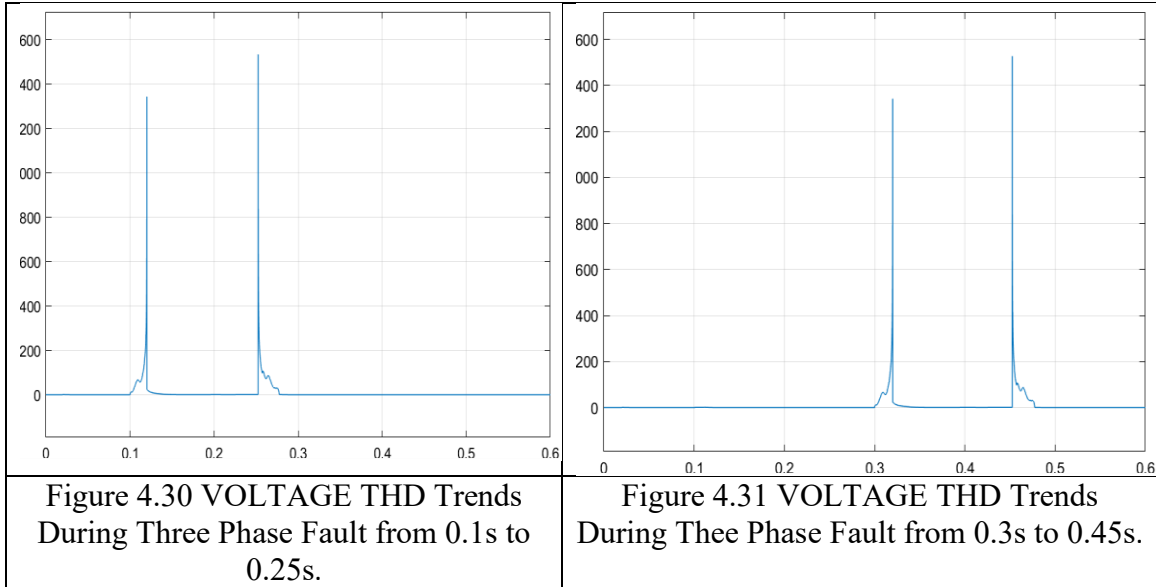


Figure 4.29 VOLTAGE THD Trends During Two Phase Fault from 0.3s to 0.45s.



H. Total harmonic current / dt Protection

Total Harmonic Current Rate of Change (THI/dt) Protection is a sophisticated protection mechanism in power systems, particularly relevant for managing power quality and detecting abnormal grid conditions such as islanding. This method monitors the rate at which the harmonic content of the current changes over time. Harmonic currents, which are currents at frequencies that are multiples of the fundamental frequency of the system (usually 50 or 60 Hz), can significantly impact the power quality and efficiency of the grid. Rapid changes in harmonic currents can be indicative of various system disturbances, including islanding.

In an islanding event, where a segment of the grid becomes isolated from the main supply, there can be abrupt fluctuations in the harmonic current within the islanded area. This is often due to the sudden disconnection from the grid's stabilizing influence and the operation of local power electronic devices, such as inverters in renewable energy systems, which can generate considerable harmonic currents.

THI/dt Protection involves setting thresholds for the acceptable rate of change of the total harmonic current. These thresholds are established based on normal operating conditions and the sensitivity of the grid and connected equipment to harmonic currents. The goal is to have a protection mechanism that can quickly respond to significant changes in harmonics, signaling potential issues like islanding or other grid disturbances, while minimizing false alarms caused by normal operational variations.

Upon detecting an excessive rate of change in harmonic currents, the THI/dt Protection system triggers appropriate protective actions. These actions may include tripping circuit breakers to isolate the affected section, adjusting the operation of harmonic filters, or modifying the control strategies of power electronic devices. This not only aids in promptly identifying and mitigating islanding and other harmonic-related issues but also helps in preserving the power quality and operational stability of the electrical system.

Implementing (*THI/dt*) Protection requires advanced measurement equipment capable of accurately detecting rapid changes in harmonic currents. Additionally, effective control and mitigation systems are needed to manage these disturbances. This protection strategy is increasingly important in modern electrical grids with substantial amounts of non-linear loads and distributed generation sources, where harmonic currents can pose significant challenges to the stability and efficiency of the power system. The Total harmonic distortion is evaluated using THD Simulink Block. If the THD of any phase current is above (5%). Then the corresponding generator will be disconnected from the system.

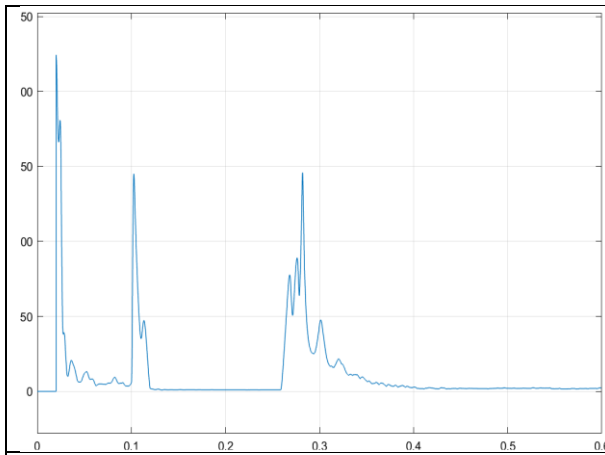


Figure 4.32 Current THD Trends During One Phase Fault from 0.1s to 0.25s.

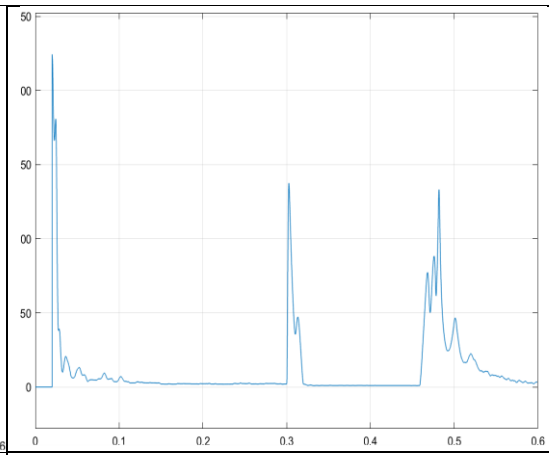


Figure 4.33 VOLTAGE THD Trends During One Phase Fault from 0.3s to 0.45s.

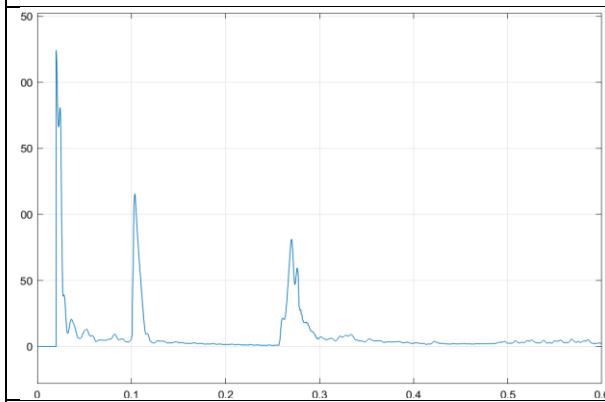


Figure 4.34 Current THD Trends During Two Phase Fault from 0.1s to 0.25s.

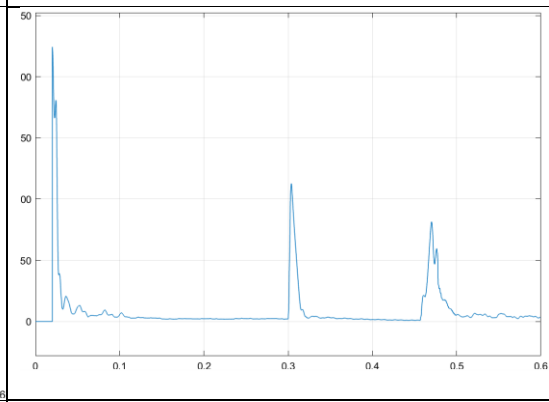


Figure 4.35 VOLTAGE THD Trends During Two Phase Fault from 0.3s to 0.45s.

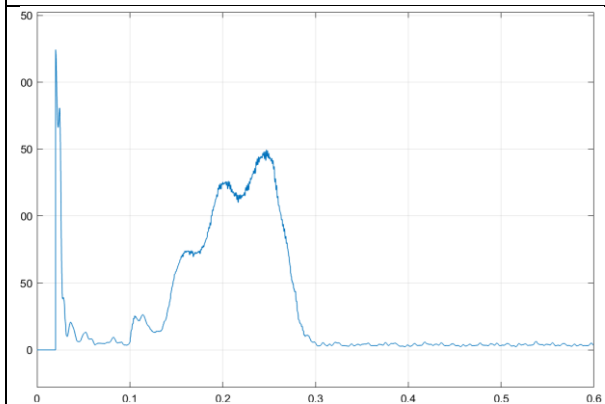


Figure 4.36 Current THD Trends During Three Phase Fault from 0.1s to 0.25s.

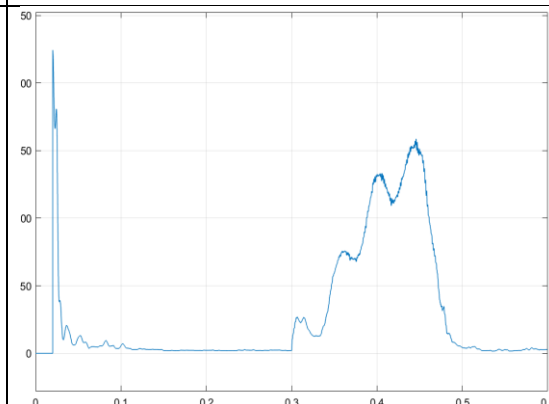


Figure 4.37 VOLTAGE THD Trends During Three Phase Fault from 0.3s to 0.45s.

Immediately after the current harmonic THD increases to more than 5%, the relay will trip to disconnect corresponding generator.

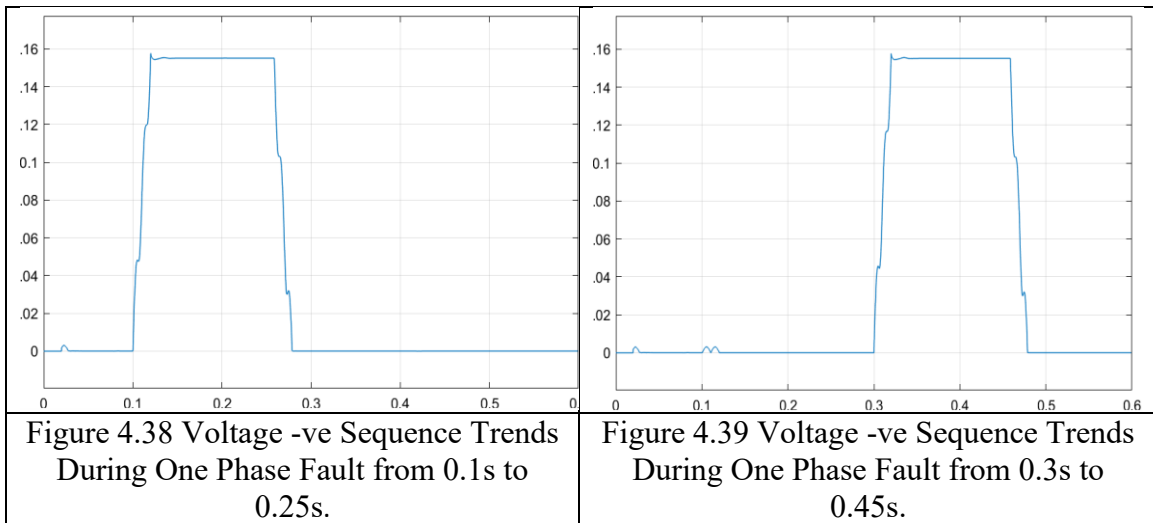
I. Voltage negative sequence/dt Protection

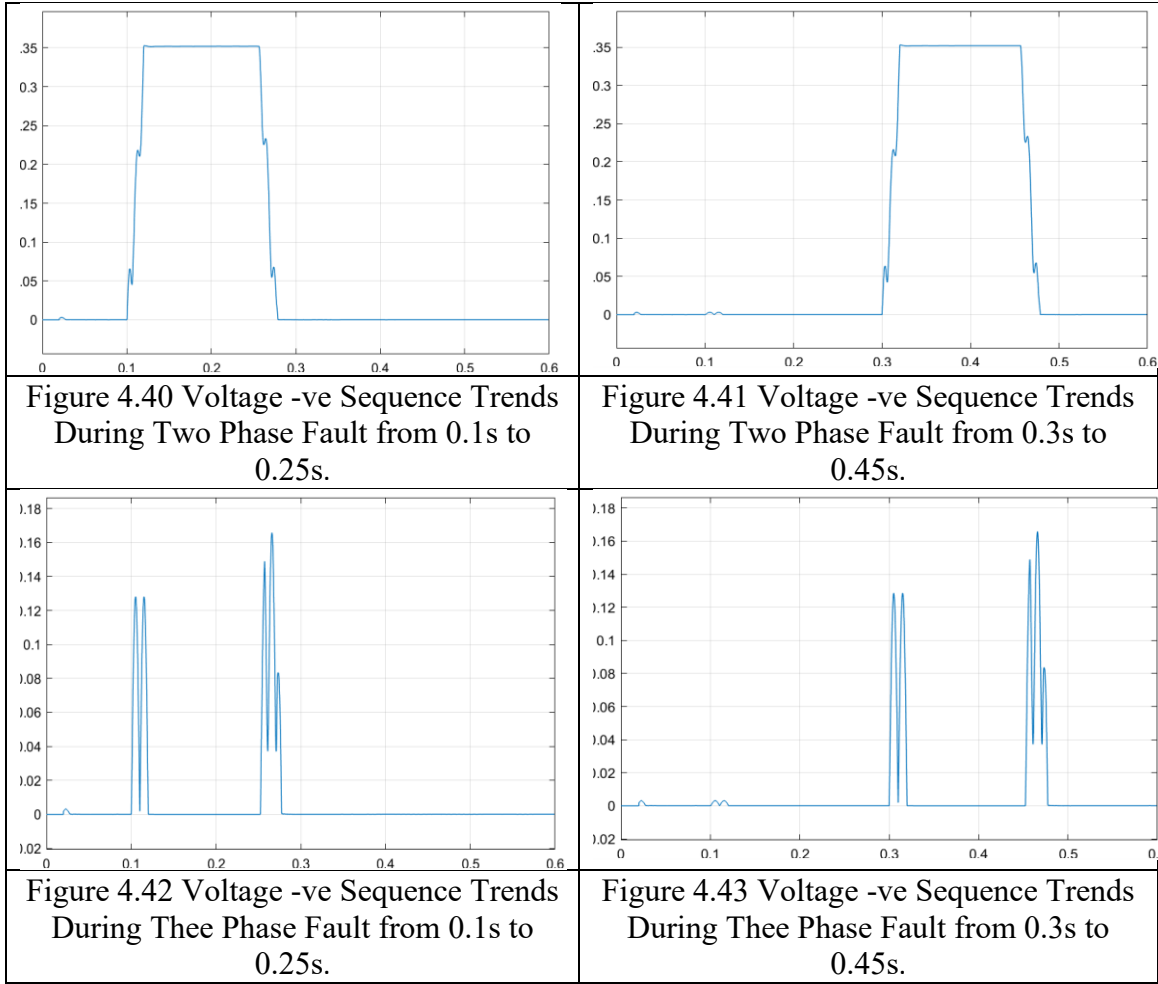
Voltage Negative Sequence Rate of Change (VNS/dt) Protection is a critical and advanced protection mechanism in electrical power systems, designed to safeguard against specific types of grid disturbances, including islanding events. This technique involves monitoring the rate at which the negative sequence component of the voltage changes over time. The negative sequence voltage, a component of the three-phase system that rotates in the opposite direction to the normal (positive sequence) voltage, can become significant during certain types of faults or unbalanced load conditions. In the context of islanding, when a portion of the grid becomes isolated from the main supply, the balance between phases can be disrupted, leading to an increase in negative sequence components. The ($\frac{VNS}{dt}$) Protection system tracks how quickly these components change. Rapid changes in the negative sequence voltage can be indicative of islanding or other abnormal grid conditions, such as unbalanced faults or phase loss situations.

The protection scheme sets thresholds for the acceptable rate of change of the negative sequence voltage, typically measured in units per second, considering the normal operational characteristics of the grid and the specific requirements for system stability and safety. The aim is to detect significant deviations that could indicate a disturbance, while avoiding false tripping due to normal operational fluctuations or minor unbalances.

Upon detecting a rate of change in the negative sequence voltage that exceeds the set thresholds, the ($\frac{VNS}{dt}$) Protection system activates necessary protective

measures. These measures might include tripping circuit breakers to isolate the affected section of the grid, adjusting load or generation balance, or activating other protective devices. This not only helps in identifying and addressing islanding scenarios but also plays a crucial role in maintaining the overall stability and reliability of the power system, particularly in scenarios where phase imbalance is a concern. Effective implementation of $\left(\frac{V_{NS}}{dt}\right)$ Protection requires sophisticated monitoring equipment capable of accurately detecting changes in the negative sequence components of the voltage, as well as responsive control systems to effectively manage these disturbances. This protection strategy is especially important in modern power systems with complex load patterns and distributed generation sources, where unbalanced conditions and their rapid detection are critical for the health and stability of the grid. The negative sequence voltage threshold is set to (0.08 pu) . If negative sequency voltage exceeds (0.08 pu) , then the corresponding generator will be disconnected from the system. Immediately after voltage negative sequence increases to more than (8%) of rated voltage, the relay will trip to disconnect corresponding generator.





J. Current negative sequence/dt Protection

Current Negative Sequence Rate of Change (CNS/dt) Protection is an advanced and crucial protection mechanism in power systems, particularly for addressing specific types of grid disturbances, including islanding events. This method focuses on monitoring the rate at which the negative sequence component of the current changes over time. Negative sequence currents, which are components of a three-phase system that rotate in the opposite direction to the normal (positive sequence) currents, typically arise during unbalanced load conditions or certain types of faults.

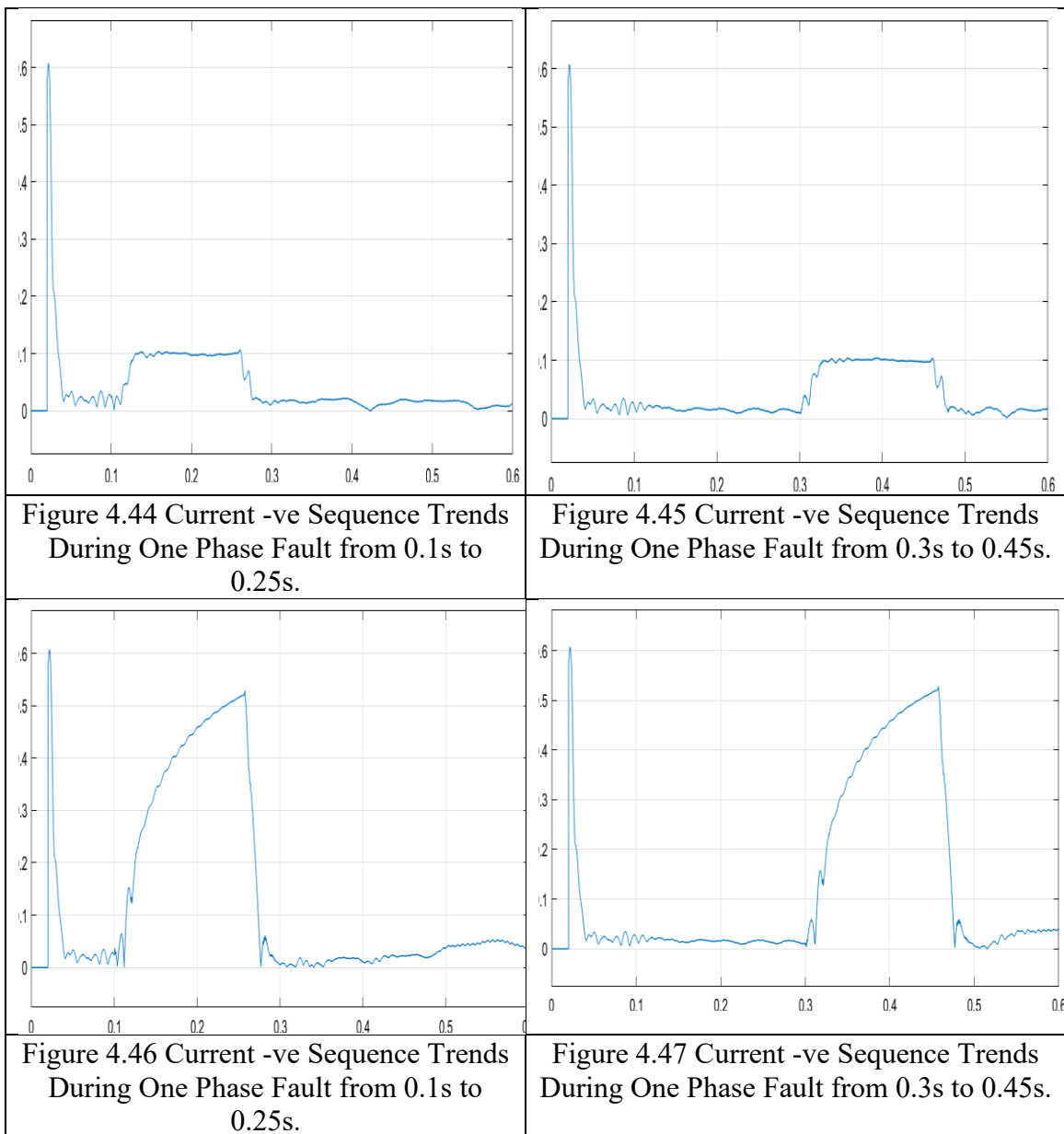
In scenarios like islanding, where a part of the grid gets isolated from the main power supply, there can be an increase in negative sequence currents due to the imbalance in the phase loads or generation within the islanded section. The (CNS/dt) Protection system is designed to track how quickly these negative sequence current components change. Rapid changes in negative sequence current are indicative of disturbances such as islanding, unbalanced faults, or phase loss.

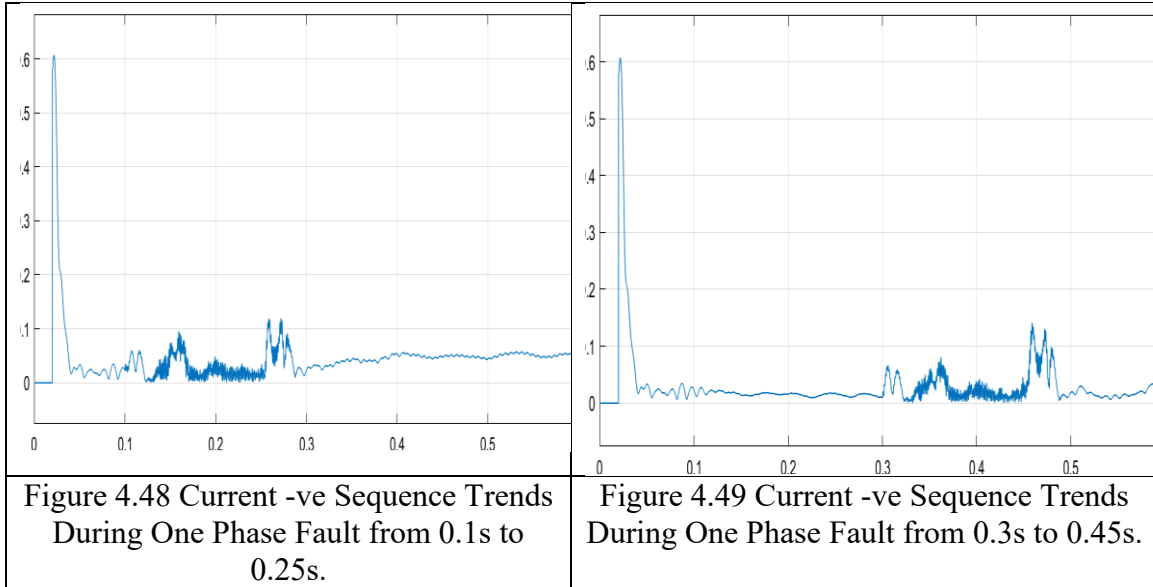
The protection strategy involves setting thresholds for the acceptable rate of change of the negative sequence current, measured in amperes per second or a similar unit. These thresholds are determined based on the normal operating conditions of the grid and are calibrated to detect significant deviations that point to potential problems, while minimizing false triggers due to normal operational fluctuations or minor unbalances.

When the (CNS/dt) Protection system detects a rate of change in negative sequence current that exceeds the established thresholds, it initiates protective actions. These actions might include isolating the affected grid section, rebalancing the load or generation, or activating other protective devices. This not only aids in promptly identifying and addressing islanding and other related issues but also helps maintain the overall stability and integrity of the power system, especially in situations where phase imbalance is a critical factor.

Implementing (CNS/dt) Protection requires sophisticated monitoring equipment capable of accurately detecting rapid changes in negative sequence currents, along with responsive control systems to manage these disturbances effectively. This protection mechanism is particularly vital in modern electrical grids with complex loads and distributed generation sources, where

detecting and managing unbalanced conditions quickly is essential for maintaining grid health and stability. The Negative sequence current is evaluated using sequence analyzer. The negative sequence current threshold is set to (0.08 pu). If negative sequence current exceeds (0.08 pu), then the corresponding generator will be disconnected from the system. Immediately after the current negative sequence increases to more than 8% of rated current, the relay will trip to disconnect corresponding generator.





4.6 Performance Management in Dynamic Dataset Generation

Dynamic datasets offer significant cost advantages over traditional static datasets, primarily through more efficient data storage and processing. Unlike static datasets that require substantial physical infrastructure, dynamic datasets are often managed in cloud-based systems. This cloud storage approach allows for scalable data management, where storage resources can expand or contract as needed, resulting in a more efficient use of resources and reduced storage costs.

Furthermore, dynamic datasets are designed for efficient processing, utilizing modern data management systems that can handle large volumes of data more swiftly. This efficiency reduces the computational resources and time required for data processing and analysis, leading to lower operational costs.

Real-time data updates enable quicker decision-making, allowing organizations to rapidly address issues, optimize processes, and capitalize on market opportunities, thus avoiding potential losses and maximizing profits. This timely decision-making process minimizes data redundancy and streamlines management, further cutting down costs associated with managing outdated or duplicated data. Moreover, the accurate and up-to-date nature of dynamic datasets ensures more efficient resource allocation or misallocation based on inaccurate data. The scalability of dynamic datasets allows organizations to adjust their data handling capabilities to current needs, avoiding unnecessary expenses associated with less flexible static datasets. Finally, the compatibility of dynamic datasets with automation and advanced business systems reduces manual data handling, further decreasing labor costs and enhancing overall economic efficiency.

4.7 Summary

The section starts by emphasizing the importance of feature extraction from Simulink Model for training and testing supervised machine learning algorithms then introduced as solutions to address limited data problems and prevent overfitting as ways to enhance training datasets by expanding attributes and size.

The issue of imbalanced data, where negative samples outweigh positive ones, is highlighted, particularly in biological data, leading to undesirable results. Strategies for evaluating and constructing models at various hierarchical levels to tackle this imbalance are suggested. The focus then shifts to designing a Convolutional Neural Network (CNN) for islanding detection

based on actual dataset parameters such as voltage, frequency, power, harmonic, and negative sequence. The CNN architecture design and data classification process are outlined as essential steps in model development. A SIMULINK model is proposed for generating datasets for islanding detection, considering different distributed generation schemes and network connections. The goal is to design an accurate and efficient islanding detection technique for various scenarios.

Performance management in dynamic dataset generation is discussed next, highlighting cost advantages over static datasets. Cloud-based storage systems are recommended for scalability and efficient data processing. Real-time updates enable quicker decision-making, reducing redundancy and optimizing resource allocation. The compatibility of dynamic datasets with automation and advanced systems is emphasized for reducing manual efforts and enhancing overall economic efficiency.

Chapter 5

Convolution Neural Networks

Topology based Islanding Detection

Techniques

Chapter 5 Convolution Neural Networks

Topology based Islanding Detection Techniques

5.1 Introduction

This research endeavors to pioneer in the field of islanding detection in power systems by leveraging the technique of transfer learning, a method traditionally not associated with this domain. Traditionally, islanding detection focuses on monitoring discrepancies in power, frequency, or other electrical parameters. However, this study proposes an innovative angle - using image analysis of datasets, a method that is relatively unexplored in this context. By employing Convolutional Neural Networks (CNNs) within the framework of transfer learning, the research aims to analyze images representing various states of power systems, including normal operation and islanding conditions.

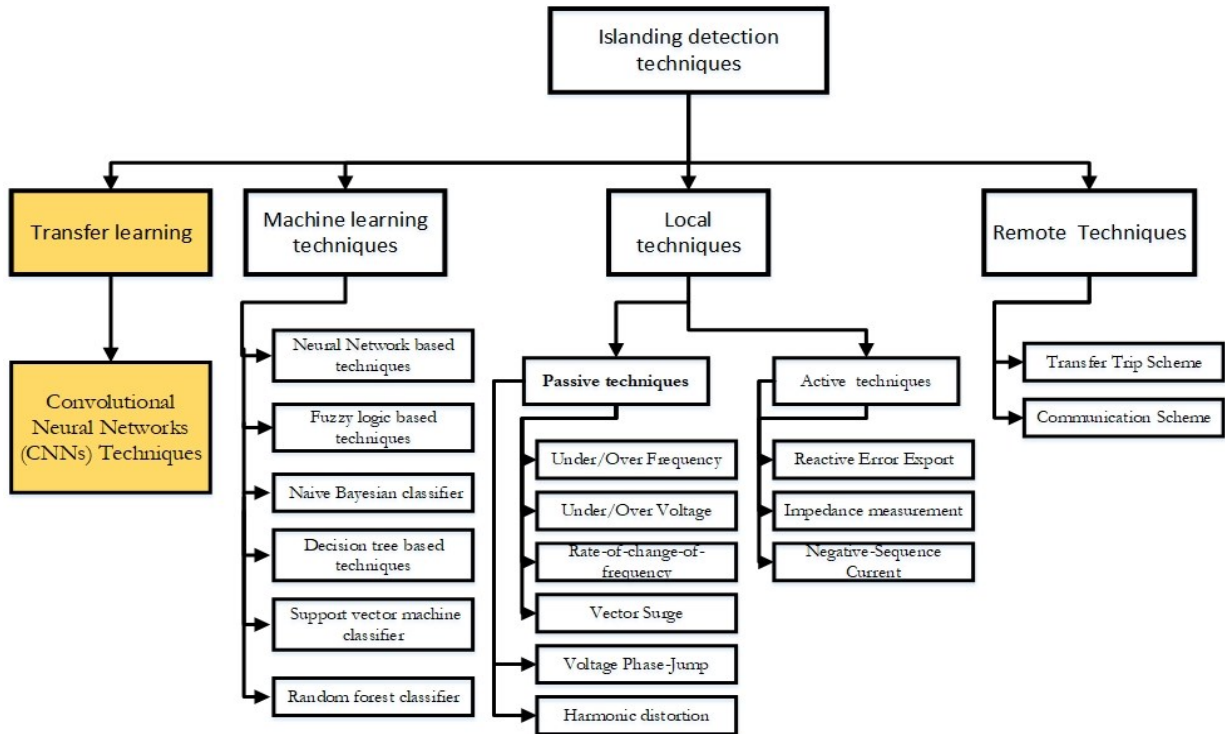


Figure 5.1 Islanding detection methods.

The core of this approach lies in utilizing pre-trained CNN models, which have been initially trained on extensive, diverse image datasets, and adapting them to recognize and classify patterns indicative of islanding events. This technique is particularly advantageous due to the detailed feature recognition capabilities features in these models through exposure to a wide array of visual inputs. By applying transfer learning, the research will bypass the intensive computational demands and extensive data requirements typically associated with training deep learning models from scratch. This strategy is relevant given the complexity and variability of islanding scenarios, where traditional detection methods might affect with accuracy or require extensive customization. Through this new approach, the research aims to establish a more robust, efficient, and accurate method of islanding detection. By analyzing image data, which could range from waveform images to effect images of equipment. The study seeks to uncover subtle and indicators of islanding events that might elude conventional detection systems. This fusion of advanced image processing techniques and power system analysis is poised to offer a fresh perspective and potentially set a new benchmark in the realm of islanding detection technology.

5.2 Transfer learning

Transfer learning is a powerful technique in the realm of deep learning, particularly when applied using Convolutional Neural Networks (CNNs), which are known for their proficiency in handling image data. This approach involves taking a pre-trained model, one that has already been trained on a large dataset (like ImageNet), and adapting it to a new, but related, problem. The effectiveness of transfer learning with CNNs lies in the fact that the initial

layers of such networks capture generic features like edges and textures that are common across various image recognition tasks. When we apply transfer learning, we can either use the entire pre-trained model as a starting point and fine-tune it on our specific dataset, or we can employ a technique known as feature extraction, where we take the convolutional base of the pre-trained model and simply add new fully connected layers that are specific to our new task. This approach is particularly advantageous when we have a limited amount of labeled data for our new task, as the pre-trained network brings with it a rich understanding of image features, significantly reducing the need for learning from scratch. By utilizing the patterns which are already recognized by the pre-trained network. The transfer learning with CNNs not only accelerates the training process but also often leads to improved performance, especially in complex tasks like object recognition, facial recognition, and medical image analysis. This method exemplifies the power of deep learning and its ability to be adapted and reapplied to a myriad of diverse and complex tasks in image processing and beyond.

It allows taking advantage of the knowledge gained from solving one problem and applying it to a second problem similar to the first, in other words reusing parts of a previously trained model in a model aimed at solving a new problem. For example, the feature extraction part of a trained vehicle recognition model can be moved to a truck-recognition model. Primarily, transfer learning technology is used in deep learning and natural language processing applications.

The primary goal of transfer learning technology is to move beyond the isolated learning approach that focuses on performing only one task, and to allow the knowledge gained from learning a task to be used to solve all related

tasks, thus developing more efficient machine learning models that have the ability to learn and gain experience in a way similar to humans. In addition, the use of a pre-trained model helps to significantly reduce the time required to train new models.

Data scientists need to have a machine learning model trained on a similar task before, so they cannot use transfer learning in every situation. However, when used, it provides better results in a shorter period of time.

Data scientists can adopt transfer learning for their operations in the following situations:

1. In some cases, data scientists may not have enough data to train their CNN models. Less data will result in lower performance, while working on a pre-trained model helps data scientists build better models.
2. Some machine learning models cannot be trained easily and can take a long time to function properly. When there is not enough time to build a new model, or when there are too many CNN tasks to handle, data scientists can prefer to adopt a similar pre-trained model that will save time rather than building a new model from scratch.

Transfer Learning advantages:

Transfer learning can provide the following benefits:

1. Better prototype: In other types of learning, we need to build a model without any knowledge. Transfer learning provides a better starting point and can perform tasks at some level without training.
2. High learning rate: Transfer learning provides a higher learning rate. During training, the problem has already been trained for a similar task.

3. Higher accuracy: With a higher starting point and learning rate, Transfer Learning provides a CNN model that enables higher precision output.
4. Faster training: Learning can achieve the required performance faster than traditional learning methods because it will benefit from a pre-trained model.

5.3 Convolutional Neural Networks

Convolutional Neural Network is a special type of Forward Feeding Neural Network that draws its inspiration from biological processes that occur in the visual lobes of the brain of living organisms and is a solution to many computer vision and artificial intelligence problems. It is called convolution because the convolutional product is an essential stage in it, and convolutional neural networks are defined as networks that use the convolution product process instead of the general product of matrices in at least one of its layers. In recent years, these networks have gained great importance in matters of classification. These network models were purposefully crafted to handle multi-dimensional matrices. Back in 1986, while investigating the visual cortex of cats, researchers Hubel and Wiesel stumbled upon overlapping sub-regions covering the entirety of the visual field. Layers function as filters, processing input images before passing them onto subsequent layers.

In 1998, LeCun Yann and Joshua Bagnio endeavored to simulate neurons in a cat's visual cortex using an artificial neural network, thus birthing the first convolutional neural network (CNN). LeNeT emerged as one of the pioneering architectures, significantly propelling the field of deep learning forward. Initially, LeNeT found primary application in character recognition tasks, such as deciphering postal codes and numbers.

Fast forward to 2012, Krizhevsky utilized CNN to secure victory in the ImageNet Classification Challenge. By training CNN on thousands of images, the successfully classified images during the test phase with a commendable error rate. Since then, CNN has undergone substantial evolution and widespread adoption, proving instrumental in solving many computer vision tasks.

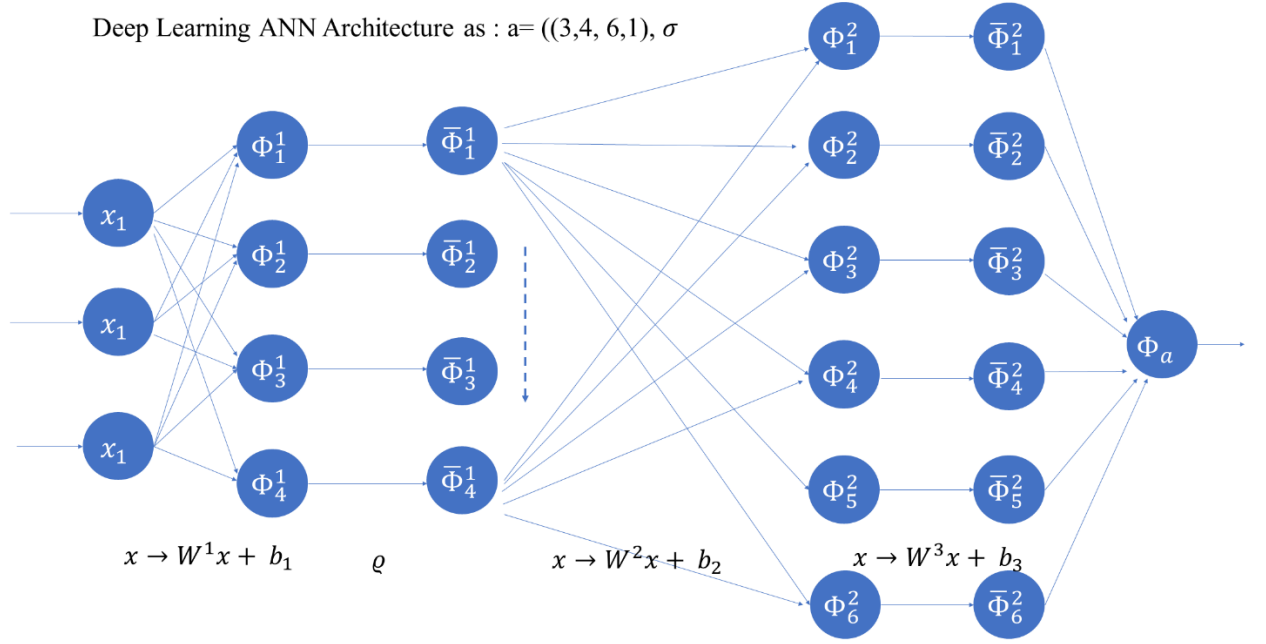


Figure 5.2 Deep Neural architecture.

The Artificial Neurons equation 5.1 can be defined as:

$$f(x_1, \dots, x_n) = \varrho(\sum_{i=1}^n x_i w_i - b) = \varrho(\langle X, W \rangle - b) \quad (5.1)$$

where

$$w = (w_1, \dots, w_n) \text{ and } x = (x_1, \dots, x_n) \quad (5.2)$$

There are a number of activation functions:

Heaviside function: $\varrho(x) = \begin{cases} 1, & x > 0, \\ 0, & x \leq 0, \end{cases}$ (5.3)

The sigmoid function:

$$\varrho(x) = \frac{1}{1+e^{-x}} \quad (5.4)$$

Rectifiable Linear Unit: $(R_eLU)\varrho(x) = \max\{0, x\}$ (5.5)

Affine Linear Maps and Weights:

Remark: Concatenating artificial neurons leads to compositions of affine linear maps and activation functions. Example: The following part of a neural network is given by:

$$\phi: \mathcal{R}^3 \rightarrow \mathcal{R}^2, \dots \quad \varphi(x) = W^{(2)}\varrho(W^{(1)}x + b^{(1)}) + b^{(2)} \quad (5.6)$$

$$W^{(1)} = \begin{pmatrix} w_{11}^1 & w_{12}^1 & 0 \\ 0 & 0 & w_{23}^1 \\ 0 & 0 & w_{33}^1 \end{pmatrix} \quad (5.7)$$

$$W^{(2)} = \begin{pmatrix} w_{11}^2 & w_{12}^2 & 0 \\ 0 & 0 & w_{23}^2 \end{pmatrix} \quad (5.8)$$

Definition of a Deep Neural Network, Part 2:

$$\theta = \theta_{i=1}^{(i)L} = ((W^{(i)}, b^{(i)}))_{i=1}^L \in {}_{i=1}^L X(\mathcal{R}^{N^\ell \times N_{i-1}} \times \mathcal{R}^{N^\ell}) \cong R^{P(N)} \quad (5.9)$$

So that ...

$$\phi_a(x, \theta) = W^1 x + b^1 \quad (5.10)$$

$$\overline{\phi^l(x, \theta)} = \varrho\left(\phi^{(l)}(x, \theta)\right), \dots \dots l \in [L - 1] \quad (5.11)$$

$$\bar{\phi}^l(x, \theta) = \varrho\left(\phi^{(l)}(x, \theta)\right), \dots \dots l \in [L - 1] \quad \text{in addition, ...} \quad (5.12)$$

$$\phi^{(l+1)}(x, \theta) = W^{(l+1)} \bar{\phi}^{(l)}(x, \phi) + b^{(l+1)} \quad \text{and } l \in [L - 1] \quad (5.13)$$

we also refer to the followings:

$W^{(l)} \in \mathfrak{R}^{N_l \times N_{l-1}} \dots$ and $b^{(l)} \in \mathfrak{R}^{N_l}$ as the wights matrix and the bias vectors. In addition, ...

$\bar{\phi}^{(l)}$ and the $\phi^{(l)}$ as the activations and pre-activations of the N_l neurons in the $l - th$ layer.

Training of Deep Neural Networks:

High-Level Set Up:

Samples: $(x_i, f(x_i))_{i=1}^m$ of a function, such as $f: \mathcal{M} \rightarrow \{1, 2, 3, \dots, \kappa\}$.

Training- and test data set. Then we need to select an ANN architecture, ...

$a = (N, \sigma)$ of a deep ANN,

Then to learn the weight matrices $W^{(l)} \in \mathfrak{R}^{N^{(l)} \times N^{(l-1)}}$. In addition, the basis vectors are: $b^{(l)} \in \mathfrak{R}^{N^{(l)}}$ by:

$$\min_{\theta} \sum_{i=1}^m l(\phi_a(x_i, \theta), f(x_i, \theta), f(x_i)) + \lambda \rho(\theta) \quad (5.14)$$

Yielding the ANN ϕ_a , This is often done by stochastic gradient descent. This is often done by stochastic gradient descent:

$$\text{Goal: } \phi_a(., \theta) \approx f$$

In this step we are now ready to train the model. A neural network type called a convolutional neural network, or CNN or Conv Net, is particularly adept at processing input with a grid-like architecture, like an image. A binary representation of visual data is a digital image. It is made up of a grid-like arrangement of pixels, each of which has a pixel value to indicate how bright and what color it should be (Mishra, 2020).

The moment we perceive an image, the human brain begins processing a massive amount of data. Every neuron has a distinct receptive field and is coupled to other neurons so that they collectively cover the whole visual field. Each neuron in a CNN processes data only in its receptive field, like how each neuron in the biological vision system responds to stimuli only in the constrained area of the visual field known as the receptive field. The layers are set up so that simpler patterns are detected early on and more complicated patterns later. One can enable sight to computers by employing a CNN (Mishra, 2020).

Convolution is a mathematical process that involves multiplying two functions to create a third function that expresses how the form of one function is altered by the other. The term "convolution" is used in CNN to refer to this mathematical activity. To extract features from a picture, two images that can

be represented as matrices are multiplied to produce an output (Gurucharan, 2022).

```
# making the deep learning function
def model():
    model = Sequential()
    model.add(Conv1D(filters=64, kernel_size=6, activation='relu',
                     padding='same', input_shape=(14, 1)))
    model.add(BatchNormalization())
    model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))
    model.add(Flatten())
    model.add(Dropout(0.1))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(5, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adam', met-
rics=['accuracy'])
    return model
```

CNN is made up of three different kinds of layers: convolutional, pooling, and fully connected (FC). A CNN architecture is created when these layers are stacked (Gurucharan, 2022). The used layers in our model are visualized in Figure (5.3). Layers are discussed below with steps:

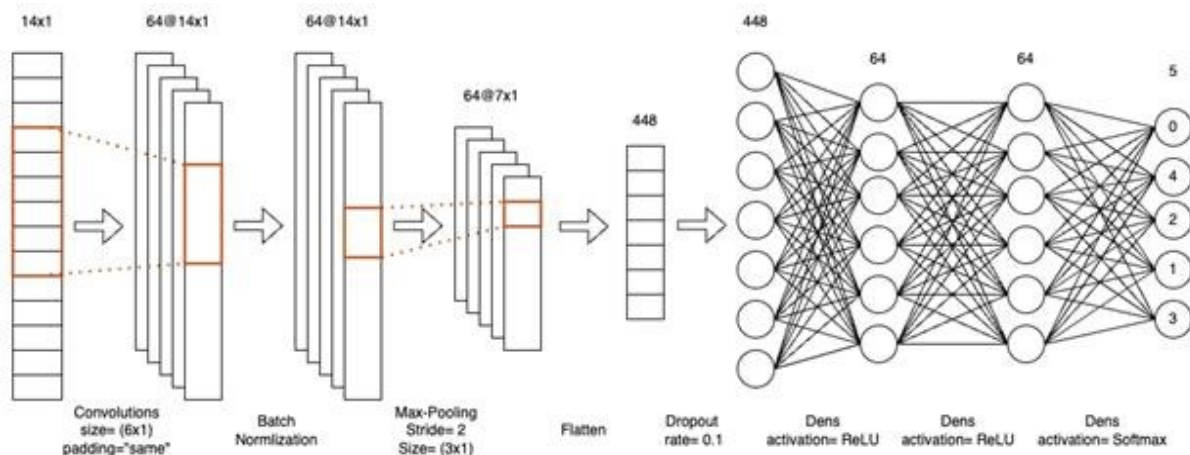


Figure 5.3 Layers of Convolutional Neural Network.

1. The Convolutional Layer:

A convolution layer serves as the foundational component in a CNN architecture. It contains an array of learnable filters, often referred to as kernels. These filters have a specific spatial dimension, defined by the filter's size, which dictates their coverage area on the input image. The process of convolution involves performing an element-by-element multiplication between the filter and the image segment it covers, followed by summing these products. This operation calculates the dot product between the filter's values and the corresponding image area. In scenarios where the input image comprises multiple channels, such as in RGB images, the same filter is systematically applied across each channel independently. Through this process, the convolution layer effectively extracts pertinent features from the input image, which are then used for further processing in the neural network.

The foundational component of the CNN is the convolution layer. It carries most of the computational load on the network (Mishra, 2020).

The first layer utilized to extract the different features from the input photos is this one. The input image and a filter of a specific size ($M \times M$) are convolved mathematically in this layer; in our scenario, the input image will be of size (14×1) . The dot product between the filter and the portions of the input image regarding the size of the filter ($M \times M$), which is in our example (6×1) , is taken by swiping the filter over the input image (Gurucharan, 2022).

$$W_{out} = \frac{W-F+P}{s} + 1 \quad (5.15)$$

From the above Formula 5.15 , we can calculate the size of the output volume if we have an input of size $(W \times W \times D)$, D_{out} number of kernels, spatial/kernel size F (a single integer or set of single integers specifying the 1D convolution

window's length), stride S (the kernel's movable size), and amount of padding P (When you pad, the output size is equal to the input size because of the same convolution) (Nkomo, 2022; Mishra, 2020).

In our case the input shape is $(None, 14, 1)$ so $(W = 14)$, and the kernel size is 6 so $F=6$, and padding is 'same' that indicates we want the output to be same size of our input, so $(W = W_{out} = 14)$, and (S) is 1 by default.

output = $(None, 14, 64)$

Figure 5.4 illustrates the steps of Convolution layer.

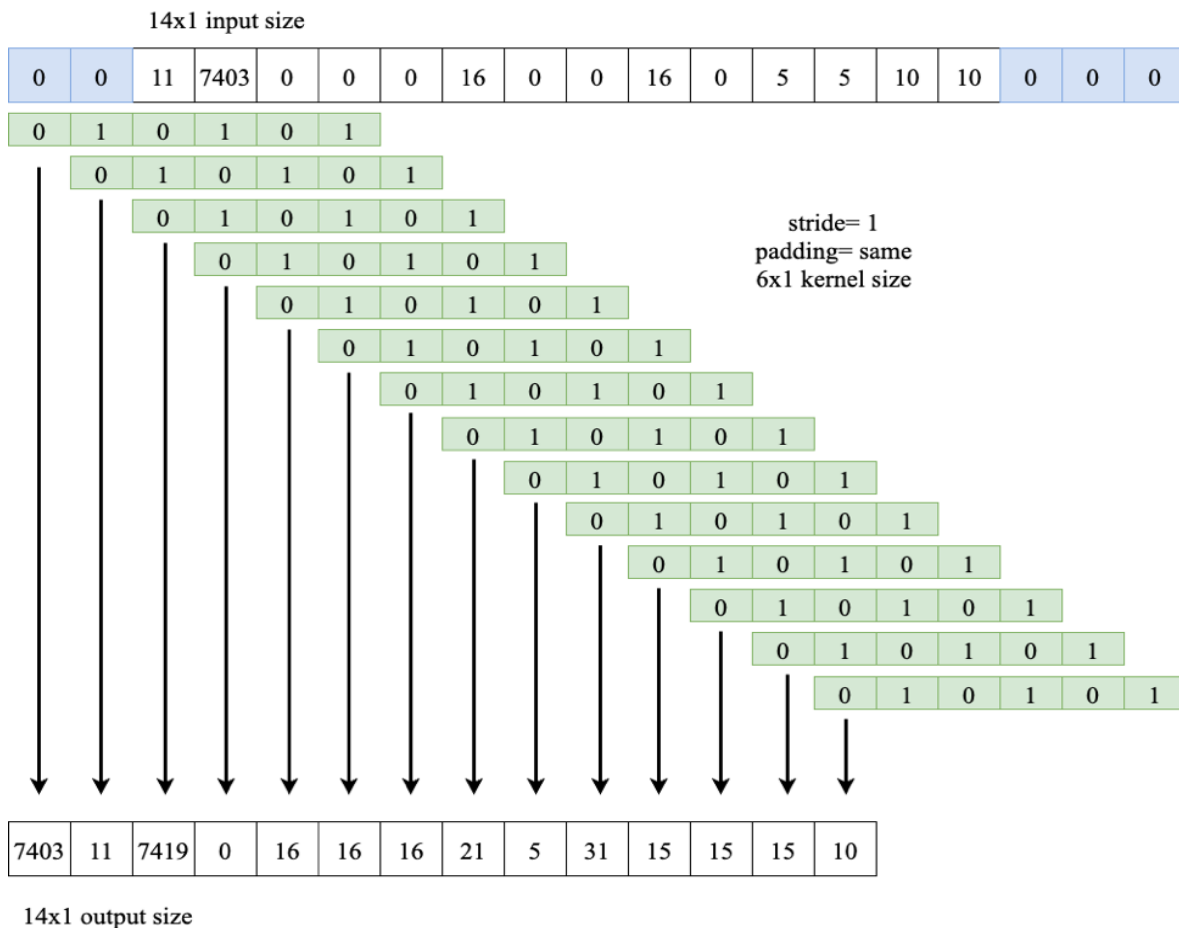


Figure 5.4: Steps of Convolution Layer.

The output is sometimes called a feature map. The data is numeric when we work with computing devices, so we use the discontinuous convolution product shown by the following relationship.

$$s(t) = \int x(a)w(t - a)da = \sum_{\sigma=-\infty}^{+\infty} x(a)w(t - a) \quad (5.16)$$

Where x is the input and w is the kernel.

The above equation 5.16 can be represented by the image and two filter A and B.

In Figure 5.3 and 5.4, an example image of size 6x6 is depicted alongside two filters of size 3x3. This illustration serves to elucidate the operations of various layers. Convolution, a fundamental mathematical operation, involves performing a dot product between the filter and the image. Essentially, it entails element-wise multiplication and addition across the entire image.

As depicted in Figure 5.3, performing element-wise multiplication and addition yields a value of 1. Subsequently, the filter slides over the image with a stride of 1, transitioning to the next position the element-wise multiplication and addition produce a value of (-1). This process continues as filter -A traverses the entire image, culminating in a feature map where all resulting values are aggregated. The feature map generated by filter-A is displayed in the last step as show in Figure 5.5.

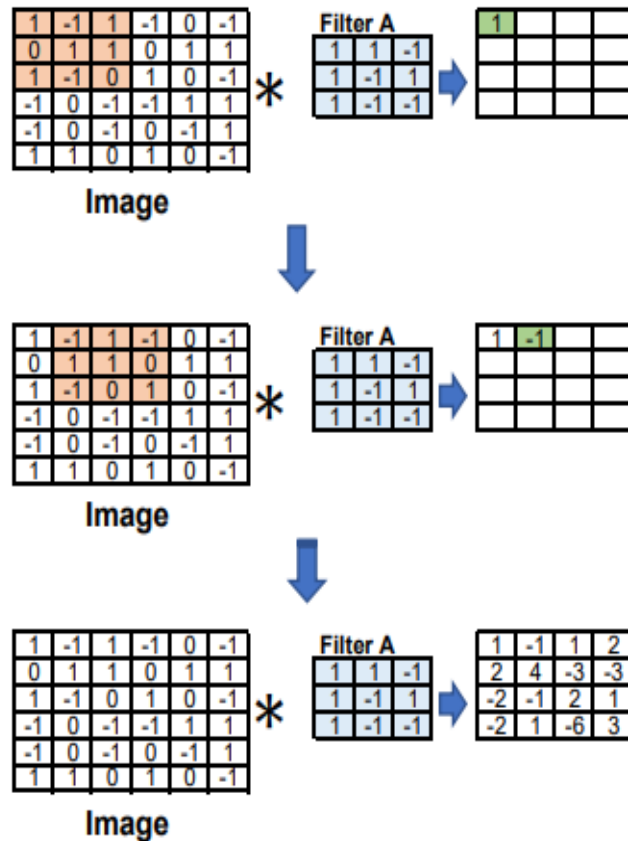


Figure 5.5 Image Convolution first step with filter A.

Likewise, a feature map for filter-B is generated and presented in Figure 5.6. The quantity of feature maps is contingent upon the number of filters employed. The selection of filter size and the number of filters in a CNN is a design decision. These parameters are meticulously chosen to optimize performance.

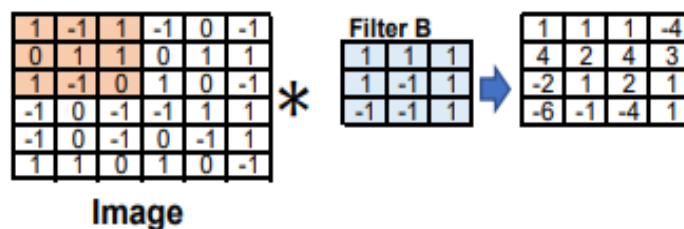


Figure 5.6 Image Convolution first step with filter B.

Therefore, this product will continue to cover every single pixel in the image as described is figure 5.7

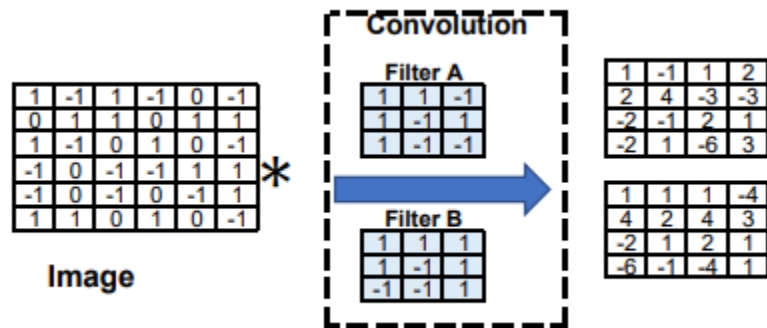


Figure 5.7 Image Convolution with two filters.

2. Activation layer:

Once the convolution process concludes, the feature map proceeds to the activation layer where an activation function is applied to each neuron, corresponding to an element of the feature map. This activation layer assumes a pivotal role in infusing non-linearity into the network's processing, a critical aspect for learning intricate patterns in data. Positioned subsequent to the convolutional layer, it employs an activation function on the output derived from the preceding layer. Frequently employed activation functions comprise ReLU (Rectified Linear Unit), Sigmoid, and Tanh. The selection of the activation function is contingent upon the specific requisites of the network and the characteristics of the data being processed.

The activation layer serves as a crucial component in converting the linear input received from the convolutional layer into a non-linear output. This transformation is instrumental in empowering the network to tackle more

intricate tasks such as image and speech recognition. Take, for example, the ReLU activation function, which zeros out all negative pixel values in the feature map, effectively directing the network's attention towards the most pertinent features. On the contrary, the Sigmoid and Tanh functions adjust the feature map values to confine within specific ranges, such as this layer outputs zero if the input is negative or retains the same number for positive values. The resulting feature map is illustrated in Figure 5.8. These adjustments are pivotal for subsequent layers to execute more nuanced and precise data processing tasks.

Instead of conducting the normalization in the raw data, batch normalization is done between neural network layers. Instead of utilizing the complete data set, mini batches are used. It accelerates training and uses faster learning rates to promote learning (Riva, 2022). The output dimension is the same as the input dimension.

$$output = (None, 14, 64)$$

The theory behind the normalization layer is demonstrated in the proceeding equations, (Peccia, 2019). The batch mean is calculated with the batch variance, below Formula 5.17 , and Formula 5.18 .

$$\mu_B = \frac{1}{m} \sum_{i=1}^m x_i \quad (5.17)$$

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2 \quad (5.18)$$

Next step is applying normalization with Formula 5.19 ,

$$\bar{x}_l = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \quad (5.19)$$

Last step is applying scale and shift to get the output of the layer with Formula 5.20.

$$y_i = \gamma \bar{x}_i + \beta \quad (5.20)$$

The concept of deep neural networks is not novel in theory; it has been proposed for a considerable period. However, its realization has been challenging due to various obstacles. One significant challenge that hindered its advancement is the issue of Vanishing Gradient.

Vanishing Gradient problem impedes or slows down the learning process, rendering dealing with deep neural networks challenging and impractical. This problem stems from the application of the backpropagation algorithm. During neural network training, weights across different layers are updated iteratively, with adjustments proportional to the derivative values:

$$\frac{\partial C}{\partial w_i}$$

w_i : The weight of layer i

C: loss function in the output layer

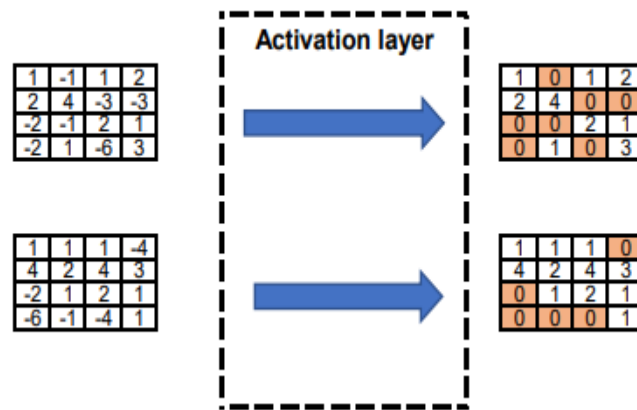


Figure 5.8 Feature map after ReLU activation application.

It is this derivative in a layer that will control the update of the weight's values, and with a mathematical approximation:

$$\frac{\partial C}{\partial w_i} \propto f'(Z^{(i)}) \cdot f'(Z^{(i+1)}) \cdot f'(Z^{(i+2)}) \dots \dots \dots \quad (5.21)$$

f: Activation function

Z^i : Neuron in layer i

The problem of vanishing gradient in neural networks comes when $f' \ll 1$ and therefore when multiplying a set of values much smaller than one, the result will become close to zero, and this leads to a very small value of the derivative, and therefore there is no update in the values of the weights.

3. Pooling Layer:

In CNN, a pooling layer is crafted to diminish the spatial dimensions (width and height) of the input volume while preserving crucial information. Usually positioned after the activation layer, this layer employs a pooling operation to shrink the feature maps produced by preceding layers. The prevalent types of pooling include Max Pooling and Average Pooling. Max Pooling entails selecting the maximum value from each segment of the input feature map, thus capturing prominent features effectively. Conversely, Average Pooling calculates the average value of each segment, yielding a more generalized representation.

By obtaining a summary statistic of the surrounding outputs, the pooling layer substitutes for the network's output at specific locations. The representation's spatial size is lowered as a result, which lowers the calculation and weighting

requirements. Every slice of the representation that the pooling operation touches is treated separately (Mishra, 2020).

A weighted average based on the distance from the central pixel is one of the pooling functions, along with the average of the rectangular neighborhood and the L2 norm of the rectangle neighborhood. However, max pooling, which reflects the highest output from the neighborhood, is the most well-liked method (Mishra, 2020). The greatest component in Max Pooling is derived from a feature map. The elements inside a predetermined sized Picture slice are averaged using the average pooling technique. Sum Pooling calculates the aggregate sum of the components in the predefined section. Convolutional Layer and Fully Connected Layer are typically connected by the Pooling Layer (Gurucharan, 2022).

$$W_{out} = \frac{W-F}{S} + 1 \quad (5.22)$$

The output volume can be calculated using Formula 5.22 if we have an activation map of size W x W x D, a pooling kernel of spatial size F, and stride S (Mishra, 2020), in our case here the output of the previous layer is to be used as the input in this layer, so W=14, F=3, and S=2. However, using the "same" padding option produces the following output shape: ***output shape = $\frac{\text{input shape}}{\text{strides}}$***

$$W_{out} = \frac{14}{2} = 7 \quad (5.23)$$

output = (None, 7, 64)

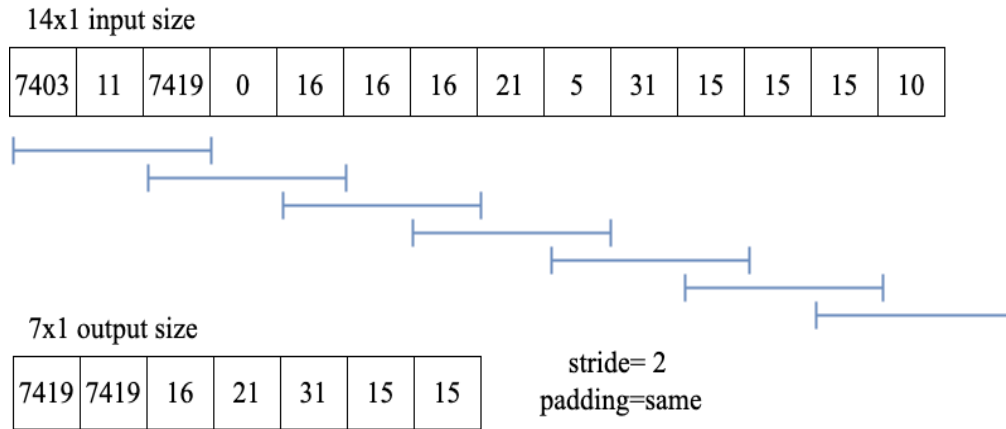


Figure 0.9 Steps of Maximum Pooling layer.

The main role of the pooling layer is to reduce computational complexity and parameter count by down sampling the input. This reduction not only helps prevent overfitting but also enhances network efficiency. By compressing the input volume, pooling layers ensure subsequent CNN layers focus on the most significant features, aiding tasks like image classification and object detection.

Pooling functions replace network outputs at specific locations with statistical summaries. For instance, Max Pooling condenses each window to a single element representing the highest value within that window. Other notable pooling operations include summation via mean calculation over a rectangular neighborhood and weighted mean summation based on distance from the neighborhood center. The output of pooling is a feature map with the same depth but altered widths and heights which can be achieved as shown in figure 5.10 Max Pool with 2x2 filters

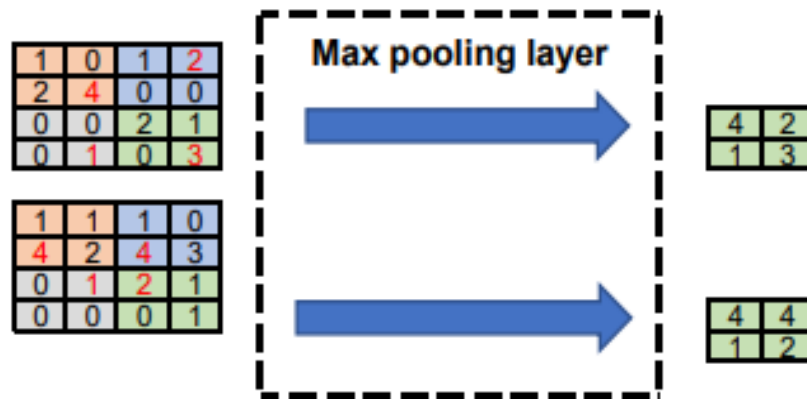


Figure 5.10 Feature map transformation following max pooling application.

4. Flatten Layer:

In CNN architecture, the flattened layer acts as a link connecting the convolutional layers to the fully connected layers. It intervenes after the prior layers (convolutional, activation, and pooling layers) have processed the input image. The primary role of the flatten layer is to convert the processed 2D feature maps into a 1D vector. This conversion is essential as the fully connected layers, typically succeeding the flatten layer, demand a linear array of features as input. The process of flattening does not involve any learning or modification of the data itself. Instead, it simply restructures the data, converting the multi-dimensional output of the preceding layers into a single, long vector. This vector retains all the spatial hierarchy and feature information extracted from the image by the earlier layers. By doing so, the flatten layer makes it feasible for the densely connected layers to perform tasks like classification, based on the comprehensive features extracted and processed in the preceding stages of the CNN. After going through the previous layers, we then make the output of the two stages in the form of a

vector that fits the input of the neural networks to be entered into the last stage of the CNN algorithm.

We have flattened and completely linked layers at the end of CNN. It must take the form of a one-dimensional linear vector. Direct inputs are not allowed to be rectangular or cubical in form.

As a result, we need layers that are fully connected and flattened. When data is converted into a 1-dimensional array for input into the next layer, it is flattened. We flatten the output of the convolutional layer to create a feature vector. It is also linked to the previous classification model, which is known as a fully connected layer, as shown in Figure (5.11).

In other words, we connect the last layer to a single line that contains all the pixel data (Jeong, 2019).

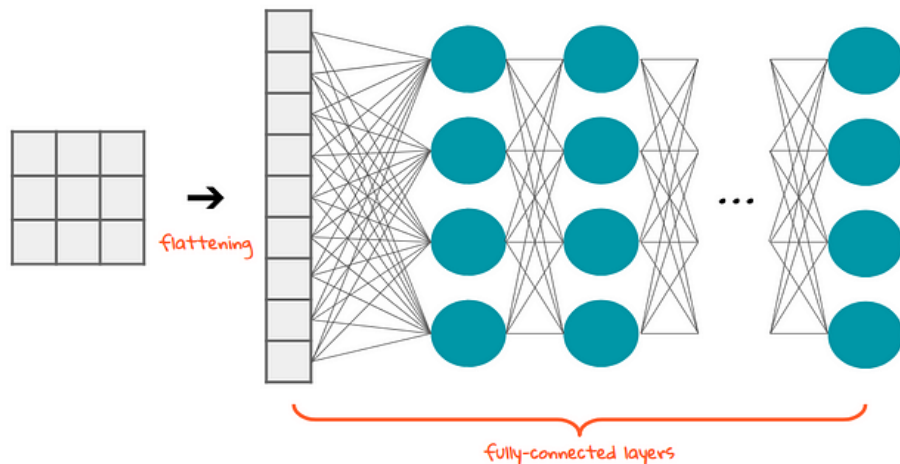


Figure 0.11 Flatten and fully connected layers, (Jeong, 2019).

By taking the previous output as an input for this layer, we got the following output:

$$output = (None, 7 \times 64) = (None, 448) \quad (5.24)$$

5. Dropout layer

A dropout layer is a particular kind of regularization method that is used to avoid overfitting and enhance generalization error in machine learning and neural network models. A dropout layer randomly removes a part of its input units during each training cycle. As a result, because it cannot rely on a single input unit to always be available, the model is compelled to acquire more reliable and generalizable properties. Any layer in a neural network model can have dropout layers added, and a hyperparameter can be used to adjust how many units will really drop out of the network (Brownlee, 2019).

$$output = (None, 448) \quad (5.25)$$

6. Dens Layer 1

Each neuron in a dense layer that is connected to the layer above it in a neural network signifies that layer is connected to the layer above it. This layer is the one that is most typically used in artificial neural network networks. Each neuron in the layer above delivers signals to the neurons in the dense layer, which multiply matrices and vectors, in a model. During matrix vector multiplication, the row vector of the output from the preceding layers is identical to the column vector of the dense layer. To multiply matrices using vectors, the row vector must have the same number of columns as the column vector (Verma, 2023).

One of the most fundamental and important parameters of the Keras dense layer, which determines the size of the dense layer's output, is units. Since it reflects the output vector's dimensions, it must be a positive integer; in this layer, the units are 64. The activation function in neural networks is a function that transforms the input values of the neurons. It adds nonlinearity to neural

network networks so that the networks can figure out how input and output values relate to one another. In this layer, we are use the ReLU activation function (Verma, 2023).

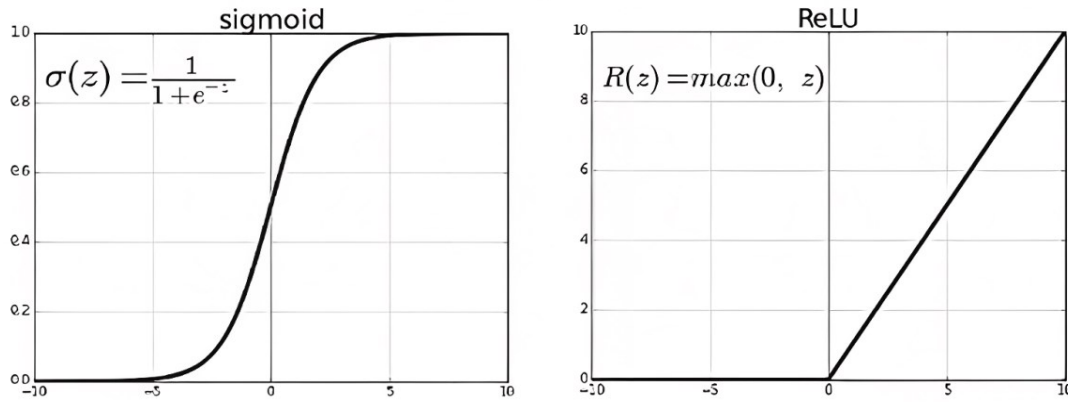


Figure 5.12 Sigmoid and ReLU functions, (Sharma, 2022).

Nowadays, the ReLU is the activation function that is employed the most globally. Figure 5.12 illustrates how the ReLU is only partially rectified (from bottom). When z is less than zero, $f(z)$ equals zero, and when z is more than or equal to zero, $f(z)$ equals z . Hence, the Range is $[0$ to infinite) (Sharma, 2022).

7. Dens Layer 2

$$output = (None, 64) \quad (5.26)$$

8. Dens Layer 3

The neural network's raw outputs are input into the SoftMax activation function, which then produces a vector of probability scores (Priya, n.d.).

- The neural network's raw outputs are represented by the vector z .
- 2.718 is the value of e .

- The expected probability that the test input will belong to class i is represented by the i -th entry in the SoftMax output vector $\text{SoftMax}(\mathbf{z})$.

The function of SoftMax is represented below in Formula 5.27:

$$\text{softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}} \quad (0.27)$$

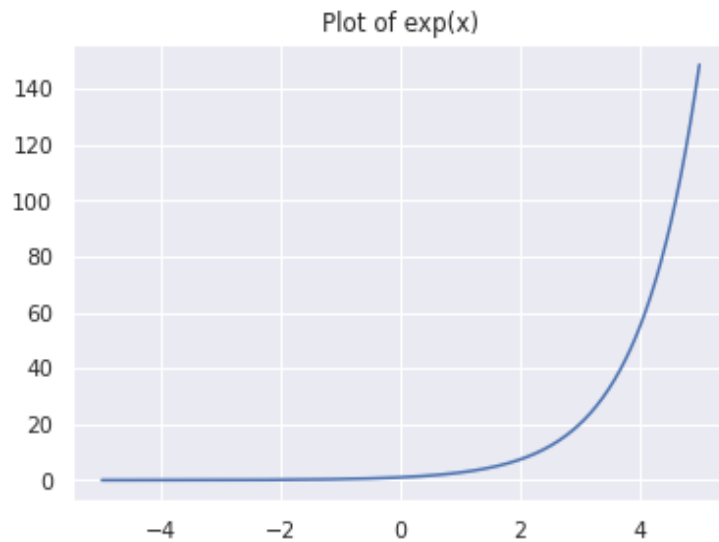


Figure5.13 Plot of exp, (Priya, n.d.).

It's clear from the plot of $\exp(x)$ that it is always a positive value, regardless of whether the input x is positive, negative, or zero, Figure (5.13), (Priya, n.d.).

As we have five classes—real, fake1, fake2, fake3, fake4—and the valid indices are 0, 1, 2, 3, and 4, $N = 5$ in our example. By assuming the given neural network's raw outputs, represented by the vector $\mathbf{z} = [0.3, 1.15, -0.7,$

5.2, 1.4]. To elaborate more on how the calculation process is done, the following calculations are done with referral to (Priya, n.d.):

1. Determine each entry's exponent.
2. Subtract the outcome of step 1 from the total exponents of all the entries.

$$\frac{e^{0.3}}{e^{0.3} + e^{1.15} + e^{-0.7} + e^{5.2} + e^{1.4}} = 0.00709$$

$$\frac{e^{1.15}}{e^{0.3} + e^{1.15} + e^{-0.7} + e^{5.2} + e^{1.4}} = 0.01659$$

$$\frac{e^{-0.7}}{e^{0.3} + e^{1.15} + e^{-0.7} + e^{5.2} + e^{1.4}} = 0.00260$$

$$\frac{e^{5.2}}{e^{0.3} + e^{1.15} + e^{-0.7} + e^{5.2} + e^{1.4}} = 0.95239$$

$$\frac{e^{1.4}}{e^{0.3} + e^{1.15} + e^{-0.7} + e^{5.2} + e^{1.4}} = 0.02130$$

$$\begin{bmatrix} 0.3 \\ 1.15 \\ -0.7 \\ 5.2 \\ 1.4 \end{bmatrix} \rightarrow \text{Softmax} \rightarrow \begin{bmatrix} 0.00709 \\ 0.01659 \\ 0.00260 \\ 0.95239 \\ 0.02130 \end{bmatrix}$$

The following conclusions can be drawn from the SoftMax output above: The greatest element in the SoftMax output vector, 0.952, is represented by the maximum value of 5.2 in the vector z of raw outputs. SoftMax's application thus maintains the relative ranking of scores. The SoftMax output vector's entries are all between 0 and 1. See how the entries of the SoftMax output aggregate to 1 in a multiclass classification problem where the classes are

mutually exclusive (Priya, n.d.): $0.0071 + 0.0166 + 0.00260 + 0.9524 + 0.02130 = 1$.

By checking the SoftMax output for our case as a following step.

The greatest value in the vector

$\text{softmax}(z) = [0.0071, 0.0166, 0.00260, 0.9524, 0.02130]$ is 0.9524.

This indicates that there is a 95.24% likelihood that the provided input is a member of class 4, or the fake3 class. The output dimension of this layer is:

$\text{output} = (\text{None}, 5)$

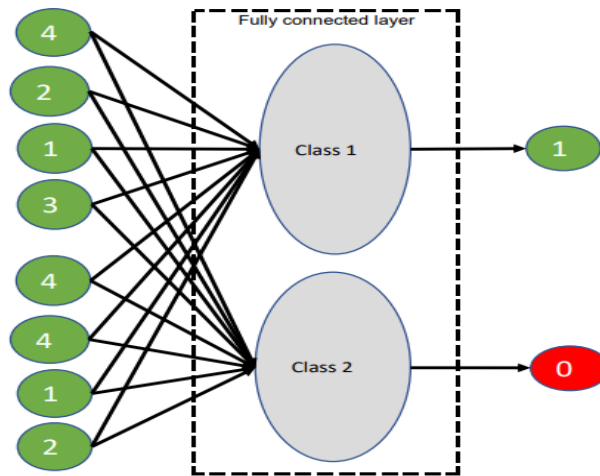


Figure 5.14 Fully connected layer with class outputs.

Throughout the training phase, the weights of neurons within the FC layer undergo adjustment via backpropagation. This adaptation is guided by the disparity between the output and the actual label or value. The fully connected layer may consist of one or multiple layers, with the final layer commonly employing a softmax activation function for classification tasks. This activation function yields probabilities for each class, as depicted in Figure

5.14. At the heart of a fully connected layer is its capacity to harness localized features, identified by earlier convolutional layers, and leverage them for overarching tasks such as object recognition in images or predictive modeling.

Figure 5.15 demonstrates the layers of CNN model.

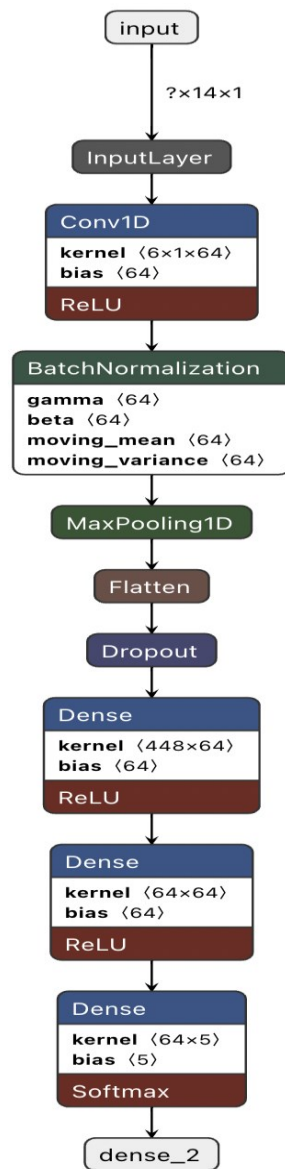


Figure 0.15 CNN Model Layers.

Serving as a decision-maker within the CNN, it amalgamates the acquired features into meaningful outputs.

5.4 The Management Approach of Using CNN Techniques for Islanding Detection

Utilizing Convolutional Neural Network (CNN) techniques for islanding detection in power systems brings a suite of advantages that significantly bolster the detection's efficiency, accuracy, and overall grid reliability. In the realm of power grid management, particularly in detecting islanding events where part of the grid is isolated due to disturbances or operational activities the precision and quick response of CNNs are unmatched. These neural networks are renowned for their high accuracy and sensitivity in pattern recognition, making them adept at identifying the nuanced changes in electrical parameters, such as voltage and frequency fluctuations, that signal an islanding event. The capability to accurately detect these changes early on is crucial, as it markedly reduces the likelihood of false positives and negatives, a common challenge with traditional detection methods.

Moreover, CNNs excel in real-time data processing, enabling them to rapidly identify islanding events as they occur. This promptness in detection is critical for the immediate initiation of corrective measures, be it the safe isolation of the affected area or its swift reconnection to the main grid. Such quick response is not only essential for maintaining the stability and safety of the power grid but also ensures minimal disruption to consumers. Additionally, CNNs demonstrate remarkable adaptability to various grid conditions. They can be trained on diverse scenarios encompassing different types of renewable energy integrations, load changes, and grid topologies. This flexibility ensures robust performance across a wide range of operational environments, a vital attribute given the increasing complexity of modern power grids with their varied energy sources and dynamic load patterns.

The implementation of CNNs for islanding detection also brings operational efficiencies. Traditional methods often require extensive parameter settings and manual threshold adjustments, which can be both time-consuming and less effective in dynamic grid environments. CNNs, through their learning capabilities, mitigate the need for such detailed parameter tuning, thus streamlining the detection process. By learning from historical data, these networks autonomously identify patterns indicative of islanding, alleviating the need for constant human intervention and adjustment. This automation not only enhances detection accuracy but also significantly reduces operational costs associated with manual monitoring and frequent recalibrations.

In terms of grid safety and stability, CNNs contribute substantially. Accurate and timely detection of islanding events prevents potential equipment damage and mitigates the risk of power outages or safety hazards to personnel and consumers. This aspect is increasingly important as grids evolve with more renewable energy sources and distributed generation, which introduce additional complexity and potential points of failure. CNNs are scalable and can be integrated seamlessly with other smart grid technologies, making them a versatile tool in the toolkit of modern grid management. As power grids grow more intricate with distributed generation sources like solar panels and wind turbines, CNNs provide an efficient means to monitor and manage these diverse and decentralized energy sources.

Furthermore, the automation of islanding detection through CNNs translates to reduced operational and maintenance costs. By minimizing false alarms and the need for extensive manual oversight, CNNs contribute to more economical grid operation. They enable utilities to allocate resources more effectively,

focusing on areas that require human expertise, while the neural network handles the routine but critical task of islanding detection.

5.5 CNN Model Algorithm Classification

Teaching a machine to understand images is a multifaceted process that blends art and science. In an era dominated by visual content, this capability has profound implications across industries, from healthcare to autonomous vehicles and beyond. The journey to enable machines to perceive and interpret images involves a series of well-defined steps that guide us toward unlocking the power of artificial intelligence. The process begins with data acquisition, where a rich and diverse dataset is curated, comprising a myriad of images that encapsulate the nuances of the real world. These images must be meticulously labeled, clearly indicating what they represent. This step is pivotal as it lays the groundwork for supervised learning. Following this, data preprocessing comes into play. It involves resizing, normalization, and data augmentation to ensure that the machine can efficiently process these visual inputs.

Next, the choice of the right model architecture is pivotal. Convolutional Neural Networks (CNNs), inspired by the human visual system, have proven to be the linchpin of image understanding. The architecture is meticulously designed, often consisting of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification.

Model training is a data-driven journey, where a split dataset is subjected to an iterative process of optimizing the model's parameters. This involves selecting an appropriate loss function, an optimizer, and a set of

hyperparameters. The goal is to minimize the disparity between the model's predictions and actual labels.

The process of teaching machines to comprehend images is a dynamic fusion of data curation, preprocessing, model development, training, and rigorous evaluation. As we embark on this journey, we bridge the gap between human perception and artificial intelligence, enabling machines to decipher the rich visual tapestry of our world. The culmination of this process brings forth the transformative potential of image understanding across a myriad of applications, propelling us further into the realm of intelligent automation and discovery.

An algorithm will be designed that simulates all cases and also simulates the relationship of the various protections with each other. The tenth different local parameters were chosen as inputs for the classification technique after measurement of the local current and voltage waveforms. The input parameters selected for this purpose are: Voltage amplitude in pu (V_{pu}), Rate of change of voltage (dV/dt), Voltage total harmonic distortion (THDV), Current total harmonic distortion (THDI), Frequency in Hz (f), Rate of change of frequency (df/dt), Rate of change of power (dP/dt), Rate of change of reactive power (dQ/dt), Voltage negative sequence distortion ($NegSV/dt$), and Current negative sequence distortion ($NegSI/dt$). The parameters selected had a high probability of showing patterns useful for classification of events. The below Fig. 5.16 summarizes the algorithm.

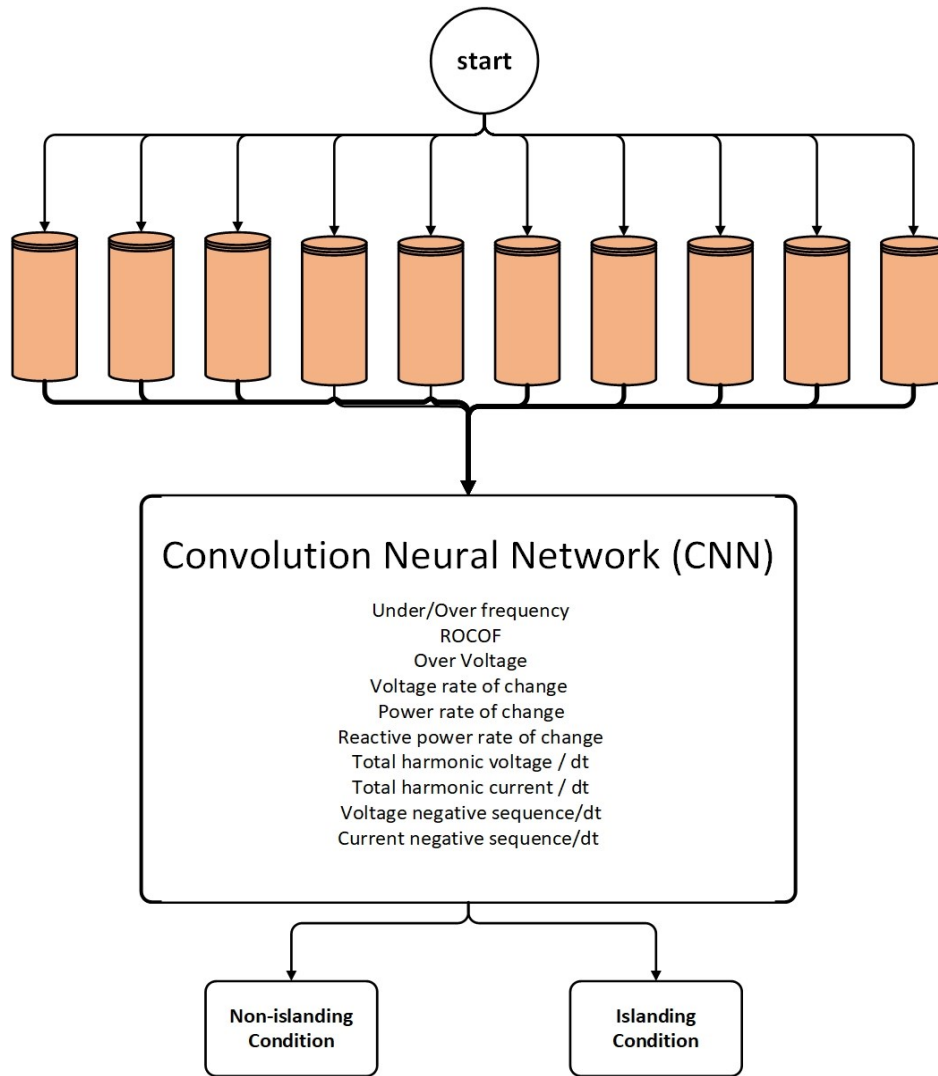


Figure 5.16 Model algorithm classification Islanding detection methods.

The Classifying islanding events, a critical task in power system monitoring, can be achieved effectively through the application of machine learning (ML) algorithms. Leveraging the power of Learning Machine (LM) algorithms, we can automate the detection of islanding occurrences, ensuring the stability and safety of the electrical grid. This process entails data acquisition, model development, training, and evaluation to create a robust and reliable classification system.

The LM algorithm, known for its ability to adapt and learn patterns from data, is selected as the model of choice. The dataset is divided into training and testing subsets, and the LM algorithm is trained to classify islanding and non-islanding events accurately.

Creating an algorithm to detect islanding events from images is a complex task that involves multiple steps. Below, I will explain in detail how to develop such an algorithm:

1- Data Collection:

- Gather a dataset of images that represent both islanding and non-islanding events. These images should ideally be captured from scenarios that mimic real-world conditions.
- Ensure that our dataset is well-labeled, with clear indications of whether each image represents islanding or non-islanding situations.

2- Data Preprocessing:

Preprocess the images to make them suitable for input to a machine learning model. Common preprocessing steps include:

- Resizing: Ensure all images have the same dimensions.
- Normalization: Scale pixel values to a consistent range.

3. Model Selection:

- Choose an appropriate machine learning model for image classification. Convolutional Neural Networks (CNNs) are

commonly used for this task due to their effectiveness in handling image data.

4. Model Architecture:

- Define the architecture of our CNN. This typically includes convolutional layers, pooling layers, fully connected layers, and an output layer.
- Configure the model to match the input image dimensions and the number of classes (2 classes in our case: islanding and non-islanding).

5. Model Training:

- Split our dataset into training, validation, and testing sets. A common split might be 70% for training, 15% for validation, and 15% for testing.
- Train the model on the training set using an appropriate loss function and an optimizer.
- Monitor the model's performance on the validation set and adjust hyperparameters if necessary.
- Continue training until the model converges and achieves satisfactory performance.

6. Model Evaluation:

- Evaluate the trained model on the testing set to assess its performance using various metrics such as accuracy and precision.

- Adjust the model or data preprocessing based on the evaluation results to improve performance if needed.

Figure 5.17 shows the interactions among those steps.

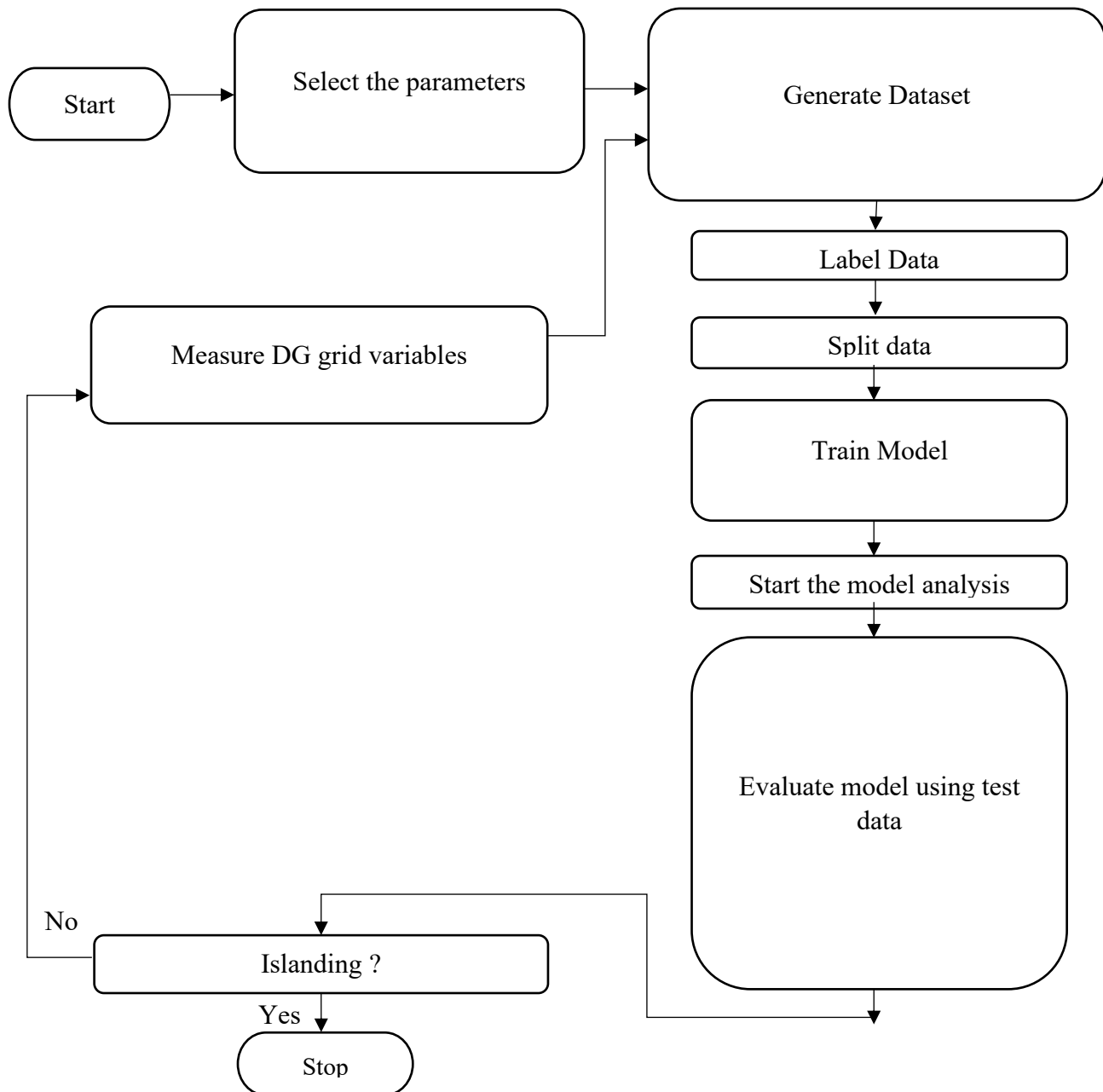


Figure 5.17 The use of machine learning to detect Islanding conditions.

The parameters selected for this study are critical to the operation and stability of power systems and include: Frequency in Hz (f), Rate of Change of Frequency (df/dt), Over Voltage, Rate of Change of Voltage (dV/dt), Rate of Change of Power (dP/dt), Rate of Change of Reactive Power (dQ/dt), Voltage Total Harmonic Distortion ($THDV/dt$), Current Total Harmonic Distortion ($THDI/dt$), Voltage Negative Sequence Distortion ($NegSV/dt$), and Current Negative Sequence Distortion ($NegSI/dt$). These parameters were chosen because they are significantly affected during islanding events and are commonly monitored in grid operations.

5.6 CNN Model Design

The study employs a dataset comprising 200 images for each protection, simulating the different conditions of islanding and non-islanding states. The images serve as input to the CNN models, which are trained to classify each state accurately. The training process involves 80% of the dataset, while the remaining 20% is used for testing and validation. This approach allows for a comprehensive evaluation of the model's performance across various scenarios and conditions typical of grid operations. The use of CNNs in this research is pivotal. Unlike traditional methods, CNNs can learn complex patterns in data, making them more adept at handling the uncertainties and variations inherent in power systems. This ability is crucial for accurately detecting islanding conditions, where slight changes in voltage or frequency can indicate a shift from normal operations. Furthermore, the use of CNNs aligns with the ongoing digital transformation in the energy sector, where there is a shift towards smarter, more data-driven approaches to grid management.

The following sections will delve into the detailed analysis of the CNN models' performance for each protection type, examining metrics such as precision, recall, f1-score, and overall accuracy. This analysis aims to assess the effectiveness of using CNNs for islanding detection in power systems and to explore the potential for implementing such advanced technologies in real-world grid operations.

The process of implementing a Convolutional Neural Network (CNN) for islanding and non-islanding event detection as shown in Figure 5.18 involves several key steps.

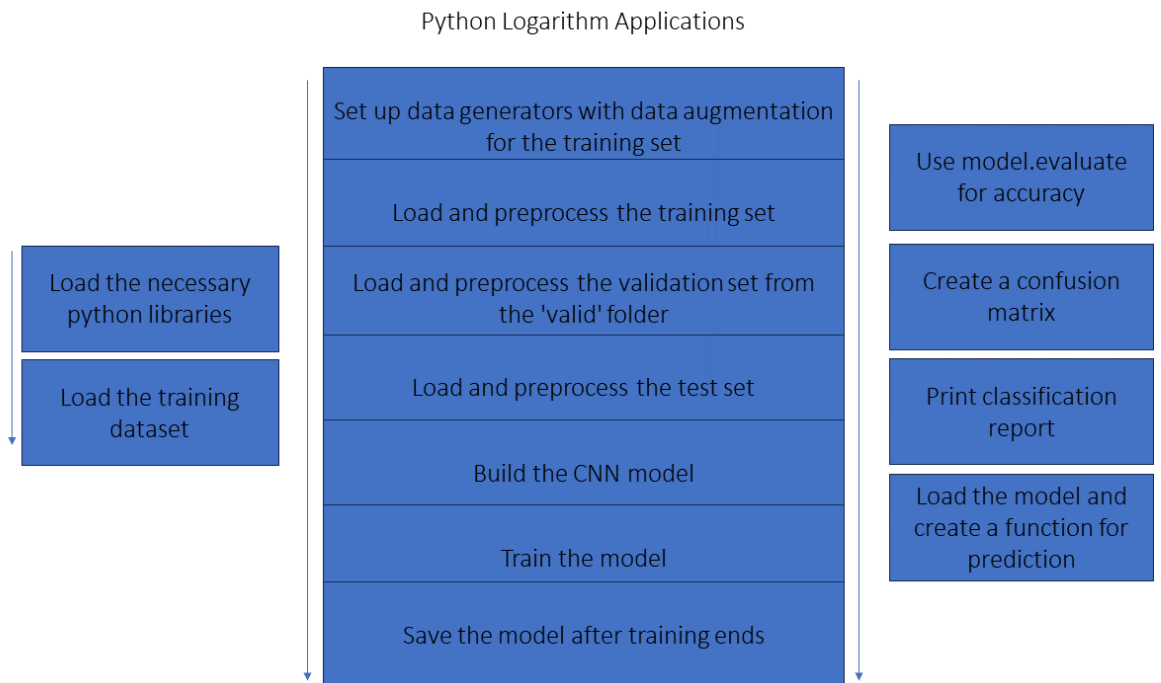


Figure 3.18 The process of implementing CNN algorithm.

Initially, essential Python libraries such as TensorFlow/Keras, NumPy, and Matplotlib are loaded to facilitate model development, data manipulation, and visualization. Subsequently, the dataset containing samples representing both

islanding and non-islanding events is loaded. Each sample in the dataset is labeled to indicate whether it corresponds to an islanding event or not, enabling supervised learning. With the dataset prepared, the CNN model is defined, specifying its architecture with convolutional, pooling, and fully connected layers tailored for event classification. The model is then trained on the loaded dataset, where it learns to differentiate between islanding and non-islanding events by adjusting its parameters iteratively through optimization algorithms. Following training, the model's performance is evaluated using various metrics like accuracy, precision, recall, and F1-score, to assess its effectiveness in correctly classifying both types of events. Finally, upon satisfactory evaluation results, the trained CNN model is deployed for real-world applications, enabling automated detection of islanding and non-islanding events in power systems, thereby enhancing grid stability and reliability. The Convolutional Neural Network (CNN) architecture outlined in Table 5.1 employs a series of layers to extract hierarchical features from input images. The initial Conv2D layer with 32 filters, each of size (3, 3), convolves across the input image with a stride of 1 and padding of 1, generating feature maps that capture local patterns.

Following this convolutional operation, a Rectified Linear Unit (ReLU) activation function is applied elementwise to introduce non-linearity, enabling the model to learn complex relationships within the data. Subsequently, a MaxPooling2D layer with a 2x2 pooling window and stride of 1 downsamples the feature maps, reducing their spatial dimensions and providing translation invariance to small variations in the input. The architectural sequence repeats with another Conv2D layer, this time employing 64 filters, maintaining the same filter size, stride, and padding. This successive convolutional layer

captures deeper and more abstract features by convolving across the output of the preceding layers. Again, ReLU activation is applied to introduce non-linearity, followed by another MaxPooling2D operation with identical parameters as before. These repeated convolutional and pooling operations create a hierarchical representation of the input image, gradually extracting features at different levels of abstraction.

Table 5.1: Designed CNN Architecture Details.

Layer	Filter Size	#filters	Stride	Padding
Conv2D	(3, 3)	32	1	1
Relu Layer				
MaxPooling2D 2×2 at stride 1				
Conv2D	(3, 3)	64	1	1
Relu Layer				
MaxPooling2D 2×2 at stride 1				
Flatten Layer				
Fully Connected Layer- Relu 128 #filters				
Fully Connected Layer- Sigmoid 1 #filters				

Table 5.2: Designed CNN Hyperparameter Details.

Hyperparameter	Value
Solver	Adam
Learning rate	0.001
Momentum	0.9
Mini-batch size	16
Maximum epochs	20
Loss function	Binary cross entropy

Once the feature maps are sufficiently abstracted, a Flatten layer reshapes the 2D feature maps into a 1D vector, preparing them for processing by fully connected layers. The first fully connected layer consists of 128 neurons, each connected to every element in the flattened feature vector.

A ReLU activation function is applied to the output of this layer, facilitating the learning of complex nonlinear relationships between features. Finally, a second fully connected layer with a single neuron and a sigmoid activation function serves as the output layer, producing a single probability value that indicates the likelihood of the input image belonging to a particular class in binary classification tasks.

Moving on to the hyperparameters listed in Table 6.2, the CNN is trained using the Adam optimization algorithm, which dynamically adjusts the learning rate during training. A learning rate of 0.001 and momentum of 0.9 are chosen to optimize convergence speed and stability. Training is conducted in mini-batches of 16 samples each, and the maximum number of training epochs is set to 20 to prevent overfitting. The binary cross-entropy loss function is employed to compute the discrepancy between the predicted probabilities and the actual class labels, guiding the optimization process towards minimizing classification errors. This comprehensive architecture, coupled with carefully selected hyperparameters, enables CNN to effectively learn and discriminate between different classes in the input data.

5.7 Summary

This The research introduces a pioneering approach to islanding detection in power systems by leveraging transfer learning, typically associated with image analysis, within Convolutional Neural Networks (CNNs). Traditional islanding detection methods focus on monitoring electrical parameters, but this study proposes using image analysis to uncover subtle indicators of islanding events. By adapting pre-trained CNN models, originally trained on diverse image datasets, the research aims to recognize and classify patterns indicative of islanding events. This technique bypasses intensive computational demands and data requirements associated with training deep learning models from scratch, offering a more efficient solution given the complexity and variability of islanding scenarios. Utilizing CNN techniques for islanding detection brings numerous advantages. CNNs excel in precision and quick response, making them adept at identifying nuanced changes in electrical parameters that signal islanding events. They demonstrate remarkable adaptability to various grid conditions, ensuring robust performance across diverse operational environments. Moreover, CNNs contribute to operational efficiencies by automating detection processes, reducing the need for manual intervention and parameter tuning. The research employs a dataset comprising images representing different islanding and non-islanding states for CNN model training and testing. Unlike traditional methods, CNNs can learn complex patterns in data, making them more suitable for handling uncertainties and variations in power systems. This aligns with the ongoing digital transformation in the energy sector, emphasizing smarter, data-driven approaches to grid management. Overall, the fusion of advanced image processing techniques and power system

analysis through CNNs is poised to set a new benchmark in islanding detection technology, offering a more robust, efficient, and accurate method for grid reliability and safety.

Chapter 6

Results and Discussions

Chapter 6 Results and Discussions

This chapter delves into the outcomes derived from the Convolutional Neural Network (CNN) models detailed in Chapter 5, which use artificial intelligence technology to discern whether a given scenario entails an islanding event or not. The methodology employed involved amalgamating all trends emanating from various protections which generated from the Simulink model, subsequently training, validating, and testing the CNN algorithm to accurately classify these trends and ascertain their islanding status. Moreover, a secondary investigation was undertaken to assess the efficacy of individual protections in isolation to identify which of parameters could be identified with greater precision. Furthermore, to provide a comprehensive comparative analysis, the utilization of time series analysis on voltage data was explored, aiming to compare between CNN image classification and time series techniques. Through these multifaceted approaches, this study seeks to shed light on the strengths and limitations of CNN-based islanding detection vis conventional methods, thereby fostering a deeper understanding of their applicability in real-world power system scenarios.

Detecting and managing these events swiftly is crucial for preventing equipment damage, ensuring consumer safety, and maintaining uninterrupted power supply. This study focuses on the development and evaluation of a Convolutional Neural Network (CNN) algorithm trained to classify islanding and non-islanding events based on critical parameters monitored in power systems. Leveraging a comprehensive dataset generated using Simulink, encompassing 1002 trends across various parameters during islanding scenarios, the CNN algorithm is trained, validated, and tested. This introduction outlines the methodology employed, including dataset

preparation, algorithm training, and performance evaluation. By exploring the efficacy of CNN algorithms in identifying islanding events, this research aims to contribute to the development of robust monitoring and detection. Among these parameters are Frequency (f), Rate of Change of Frequency (df/dt), Over Voltage, Rate of Change of Voltage (dV/dt), Rate of Change of Power (dP/dt), Rate of Change of Reactive Power (dQ/dt), Voltage Total Harmonic Distortion ($THDV$), Current Total Harmonic Distortion ($THDI$), Voltage Negative Sequence Distortion ($NegSV/dt$), and Current Negative Sequence Distortion ($NegSI/dt$). Each parameter encapsulates essential aspects of grid performance and health, offering insights into variations, distortions, and imbalances that can potentially precipitate grid instability and equipment damage. The use of Simulink to generate a dataset of 1002 trends, reflecting various parameters during islanding scenarios, lays a strong foundation for in-depth analysis. Leveraging this dataset, a Convolutional Neural Network (CNN) algorithm is trained to differentiate between islanding and non-islanding events based on parameter trends. To ensure CNN's accuracy, the dataset is divided into three groups: training, validation, and testing. The training set, comprising 414 islanding and 280 non-islanding trends, allows the algorithm to grasp the distinguishing features of each class. Subsequently, the validation set, with 58 islanding and 38 non-islanding trends, fine-tunes the model to prevent overfitting. Finally, the test set, consisting of 131 islanding and 81 non-islanding trends, evaluates the model's performance on unseen data. The resulting classification report provides insights into the CNN's precision, recall, and F1-score, indicating its effectiveness in event classifications for power grid management.

6.1 Analysis of all islanding protection Results

The evaluation of the Convolutional Neural Network (CNN) model's effectiveness in detecting islanding conditions based on the parameters provided yields insightful findings. According to the classification report, the model exhibits a precision of 0.9412 for Islanding and 0.9605 for Non-Islanding, along with a recall of 0.9771 for Islanding and 0.9012 for Non-Islanding. The corresponding f1-scores are 0.9588 for Islanding and 0.9299 for Non-Islanding, with an overall accuracy of 94.81%.

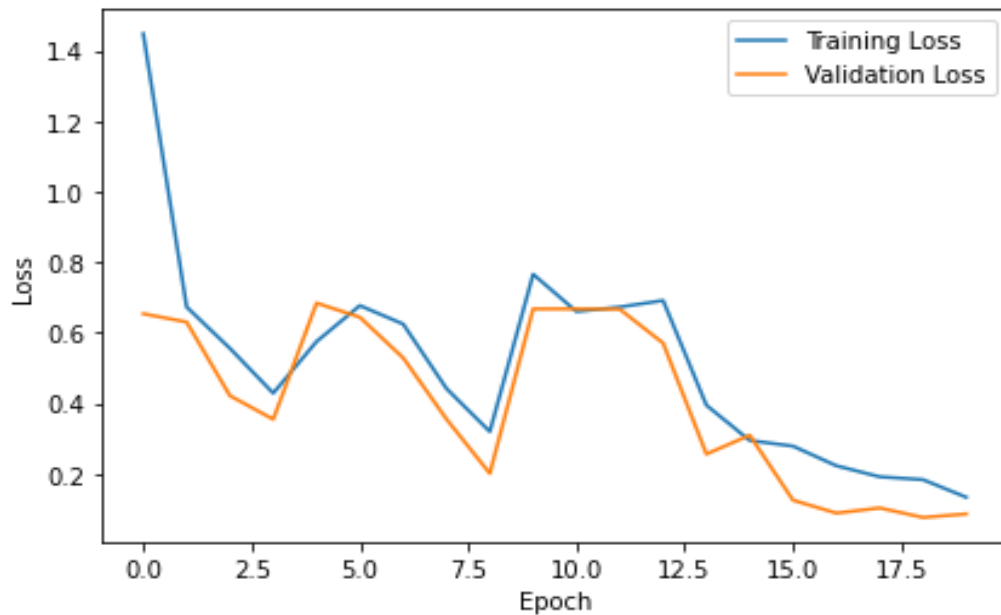


Figure 6.1 Plot training and validation history of islanding protections
Classification.

The high precision values for both Islanding and Non-Islanding classes indicate that the model's predictions are accurate and reliable. A precision of 0.9412 for Islanding suggests that when the model predicts an islanding event, it is correct approximately (94.12%) of the time. Similarly, a precision of

0.9605 for non-Islanding signifies a high level of accuracy in identifying non-islanding conditions.

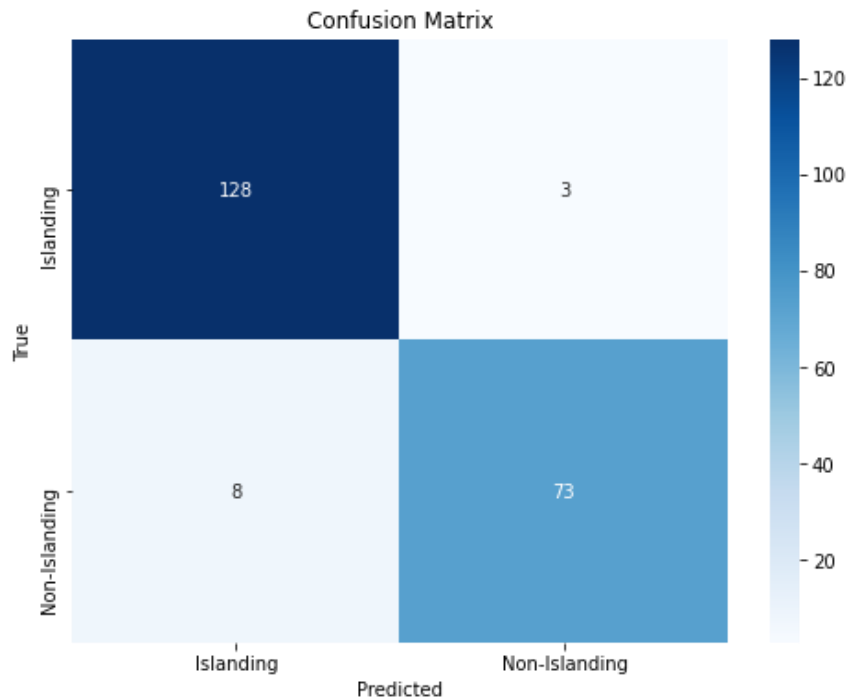


Figure 6.2 Confusion Matrix of islanding protections Classification.

The recall values of 0.9771 for Islanding and 0.9012 for Non-Islanding indicate the model's ability to correctly identify instances of each class. A recall of 0.9771 for Islanding implies that the model successfully identifies 97.71% of actual islanding events, while a recall of 0.9012 for non-Islanding suggests that 90.12% of actual non-islanding events are correctly identified by the model.

Table 6.1 Classification Report of Frequency Classification.

Classification Report:				
	precision	recall	f1-score	support
Islanding	0.9412	0.9771	0.9588	131
Non-Islanding	0.9605	0.9012	0.9299	81
accuracy			0.9481	212
macro avg	0.9509	0.9392	0.9444	212
weighted avg	0.9486	0.9481	0.9478	212

The f1-scores, which balance precision and recall, are 0.9588 for Islanding and 0.9299 for Non-Islanding. These scores indicate that the model achieves a harmonious balance between precision and recall for both classes, with slightly higher scores for Islanding.

The overall accuracy of 94.81% demonstrates the model's strong performance in accurately classifying islanding and non-islanding events. However, it's essential to note that while the model performs exceptionally well, there's still room for further improvement.

In summary, the CNN algorithm demonstrates high precision, recall, and F1-score for both islanding and non-islanding classes, indicating its effectiveness in accurately classifying the events. The overall accuracy of 94.81% suggests that the model performs well in distinguishing between islanding and non-islanding situations based on the selected parameters. The CNN report demonstrates the feasibility of utilizing CNN algorithms for the classification of islanding events in power systems based on critical parameters. The high-performance metrics obtained indicate the potential for practical implementation of such algorithms for real-time monitoring and detection of islanding events, thus contributing to the stability and reliability of power

systems. Further research and validation may be warranted to assess the robustness and scalability of the proposed approach across different operational conditions and system configurations.

6.2 Analysis of Frequency in Hz (f) Results

The analysis of the Convolutional Neural Network (CNN) model's performance for detecting islanding conditions using Frequency in Hz (f) reveals nuanced insights. The classification report indicates a precision of 0.7059 for Islanding and 1.0000 for Non-Islanding, a recall of 1.0000 for Islanding and 0.3750 for Non-Islanding, an f1-score of 0.8276 for Islanding and 0.5455 for Non-Islanding, and an overall accuracy of 75%.

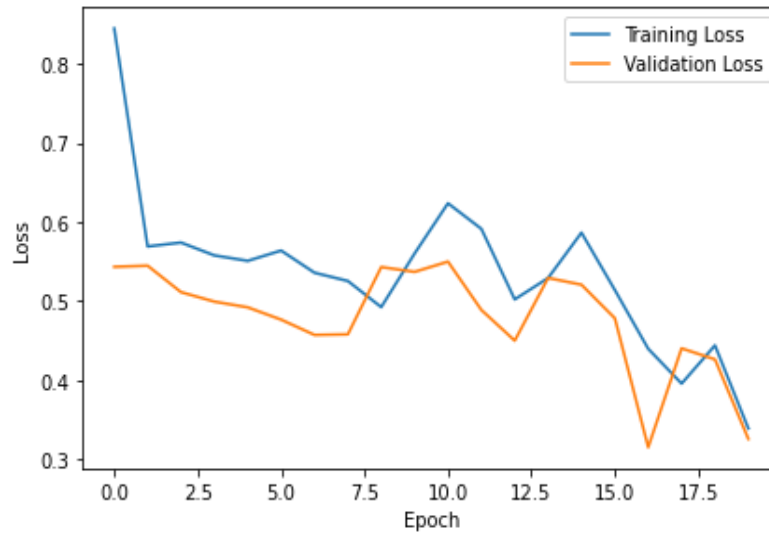


Figure 6.3 Plot training and validation history of Frequency Classification.

The high precision in non-Islanding detection (1.0000) suggests that when the model predicts a Non-Islanding event, it is almost always correct. However,

the lower precision for Islanding (0.7059) indicates a relatively higher rate of false positives – cases where the model incorrectly predicts islanding. The recall of 1.0000 for Islanding is significant as it means the model successfully identified all actual islanding events. Conversely, the low recall for non-Islanding (0.3750) is a concern, pointing to a considerable number of false negatives – instances where actual non-islanding conditions were not detected by the model.

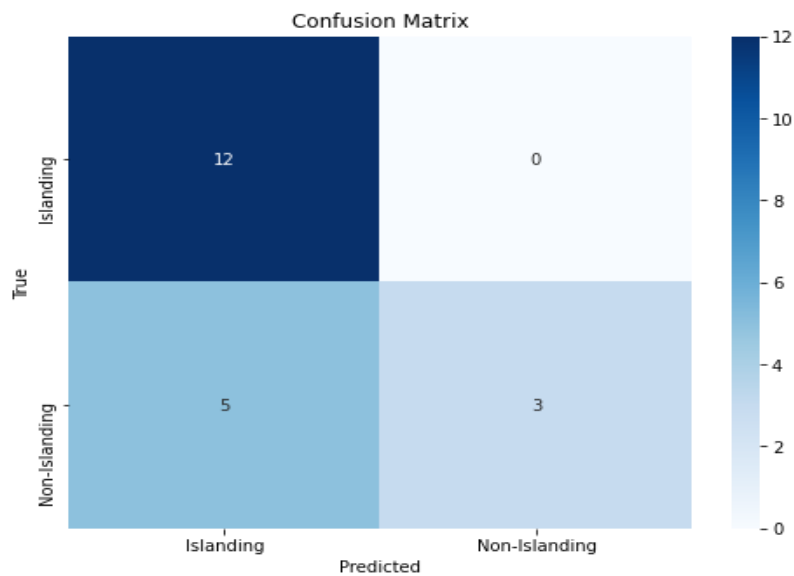


Figure 6.4 Confusion Matrix of Frequency Classification.

The f1-score, which balances precision and recall, is quite high for Islanding (0.8276) but moderate for non-Islanding (0.5455). This disparity suggests that while the model is quite reliable in identifying islanding events, its ability to correctly classify non-islanding events is less consistent.

Table 6.2 Classification Report of Frequency Classification.

Classification Report:					
	precision	recall	f1-score	support	
Islanding	0.7059	1.0000	0.8276	12	
Non-Islanding	1.0000	0.3750	0.5455	8	
accuracy			0.7500	20	
macro avg	0.8529	0.6875	0.6865	20	
weighted avg	0.8235	0.7500	0.7147	20	

An overall accuracy of 75% indicates a respectable level of model performance but also room for improvement. The high rate of false negatives in non-Islanding conditions significantly impacts this accuracy. This performance indicates that the model is more tuned towards identifying islanding conditions, potentially at the cost of misclassifying some non-islanding situations. From a practical standpoint, this tendency could lead to unnecessary grid stabilization measures being deployed, impacting operational efficiency. To improve, the model may require a more balanced training dataset or adjustments in its feature recognition layers to better distinguish between islanding and non-islanding conditions. Fine-tuning the model parameters, such as the threshold for classification, might also help in reducing the false negatives in non-Islanding detection.

In summary, while the CNN model shows strong potential in detecting Frequency-based islanding events, careful recalibration and further training are necessary to enhance its reliability and accuracy, particularly in non-islanding scenarios.

6.3 Analysis of Rate of Change of Frequency (df/dt) Results

The analysis of the CNN model's performance for detecting islanding conditions using the Rate of Change of Frequency (df/dt) provides a deeper understanding of its capabilities. The classification report for this protection shows a precision of 0.7857 for Islanding and 0.8333 for Non-Islanding, a recall of 0.9167 for Islanding and 0.6250 for Non-Islanding, an f1-score of 0.8462 for Islanding and 0.7143 for Non-Islanding, and an overall accuracy of 80%.

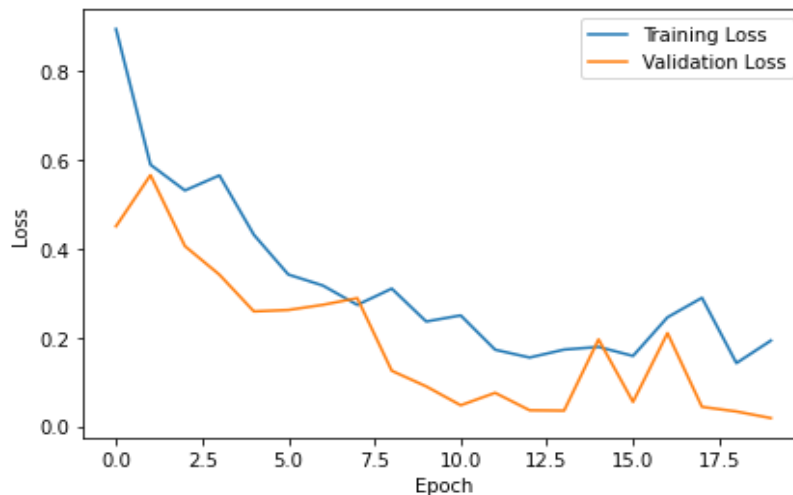


Figure 6.5 Plot training and validation history of Rate of Change of Frequency.

The precision values for both Islanding (0.7857) and non-Islanding (0.8333) are relatively high, indicating that the model is quite accurate when it predicts either state. However, the recall scores present a more nuanced picture. The recall for Islanding (0.9167) is impressive, showing that the model successfully identifies most of the islanding events. In contrast, the recall for

non-Islanding (0.6250) is moderately high, suggesting that the model misses a significant portion of non-islanding events, leading to false negatives.

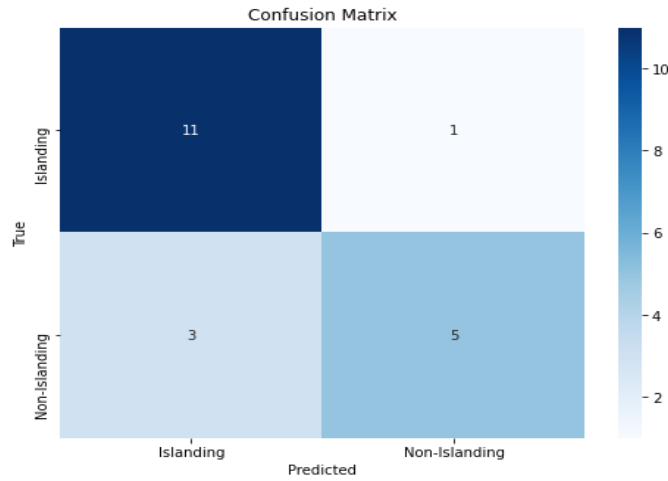


Figure 6.6 Confusion Matrix of Rate of Change of Frequency Classification.

The f1-scores, which harmonize precision and recall, are quite good for both Islanding (0.8462) and non-Islanding (0.7143). These scores indicate a balanced performance of the model in both detecting islanding events and avoiding false islanding alarms, albeit with a slightly better performance in detecting islanding conditions.

Table 6.3 Classification Report of Rate of Change of Frequency Classification.

Classification Report:				
	precision	recall	f1-score	support
Islanding	0.7857	0.9167	0.8462	12
Non-Islanding	0.8333	0.6250	0.7143	8
accuracy			0.8000	20
macro avg	0.8095	0.7708	0.7802	20
weighted avg	0.8048	0.8000	0.7934	20

An overall accuracy of 80% is a strong indication of the model's efficacy. This figure demonstrates a robust performance in differentiating between islanding and non-islanding conditions, especially compared to the first protection (Frequency in Hz). This performance highlights the model's capability in utilizing the rate of change of frequency to detect islanding conditions effectively. The slightly lower recall for non-Islanding implies that there is still a margin for improving the model's sensitivity to non-islanding scenarios. Enhancing the model might involve refining the input features to capture more subtle changes in df/dt that differentiate non-islanding events or adjusting the model's threshold settings for classifying an event as non-islanding. The balance between precision and recall also suggests that the model is relatively well-tuned but could benefit from a more diversified training dataset that includes a wider range of non-islanding scenarios. This expansion would help the model learn a broader spectrum of patterns, potentially increasing its recall for non-Islanding without compromising the precision.

In summary, the CNN model demonstrates a commendable capability in using df/dt for islanding detection, with a good balance in identifying both islanding and non-islanding events. With targeted improvements, especially in enhancing non-islanding detection, the model could achieve even higher levels of accuracy and reliability.

6.4 Analysis of Over Voltage Results

The evaluation of the CNN model's performance for detecting islanding conditions in the context of Over Voltage protection is quite remarkable. The classification report reflects perfect scores across all metrics: a precision of

1.0000 for both Islanding and Non-Islanding, a recall of 1.0000 for both categories, an f1-score of 1.0000 for both, and an overall accuracy of 100%.

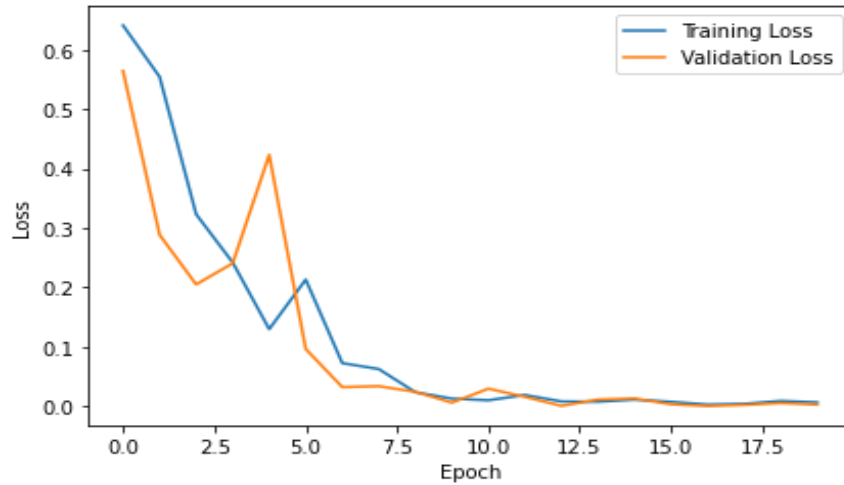


Figure 6.7 Plot training and validation history of Over Voltage Classification.

The precision of 1.0000 for both Islanding and Non-Islanding indicates the model's exceptional accuracy in predicting both conditions. It means that every time the model predicts an islanding or a non-islanding event, it is correct. Similarly, the recall of 1.0000 for both categories demonstrates that the model successfully identifies all actual islanding and non-islanding events without missing any.

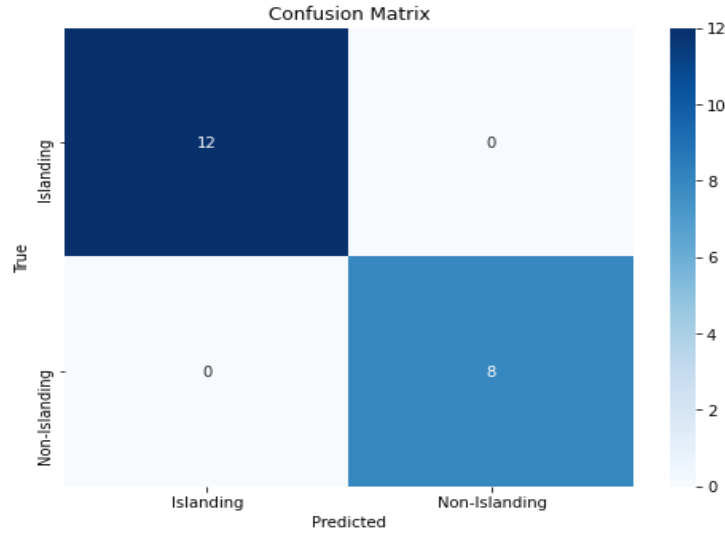


Figure 6.8 Confusion Matrix of Over Voltage Classification.

The perfect f1-scores of 1.0000 for both Islanding and Non-Islanding underscore a flawless balance between precision and recall. This metric confirms the model's ability to classify the events accurately without any trade-offs between identifying true positives and avoiding false positives.

An accuracy of 100% sets a high standard, indicating that the model performs exceptionally well in differentiating between islanding and non-islanding conditions under Over Voltage scenarios.

This remarkable performance suggests that Over Voltage conditions provide clear and distinguishable patterns that the CNN model can easily learn and identify. Such high efficacy in detection is crucial for power system stability, as over voltage situations can lead to equipment damage and safety risks if not promptly and accurately addressed.

Table 6.4 Classification Report of Over Voltage Classification.

Classification Report:					
	precision	recall	f1-score	support	
Islanding	1.0000	1.0000	1.0000	12	
Non-Islanding	1.0000	1.0000	1.0000	8	
accuracy	1.0000			20	
macro avg	1.0000	1.0000	1.0000	20	
weighted avg	1.0000	1.0000	1.0000	20	

However, while the results are outstanding, it is essential to consider the potential of overfitting, where the model performs exceptionally well on the test data but might not generalize as effectively on real-world, unseen data. Ensuring the model's robustness involves testing it under various scenarios and potentially expanding the dataset to include more diverse over voltage conditions.

Moreover, perfect scores also bring into question the complexity and variability of the test data. It's important to verify that the dataset adequately represents the full spectrum of real-world conditions, including subtle and borderline cases that might challenge the model more rigorously.

In conclusion, the CNN model's performance in detecting islanding conditions in Over Voltage scenarios is exemplary, demonstrating the potential of machine learning in enhancing grid safety and reliability. This success, however, should be tempered with considerations about the model's ability to generalize and its performance against a broader range of real-world scenarios. Further testing and validation are advisable to confirm the model's effectiveness in operational environments.

6.5 Analysis of Rate of Change of Voltage (dV/dt) Results

The analysis of the CNN model's performance in detecting islanding conditions using the Rate of Change of Voltage (dV/dt) parameter provides valuable insights into its applicability in power system monitoring. The classification report shows a precision of 1.0000 for Islanding and 0.9000 for Non-Islanding, a recall of 0.9167 for Islanding and 1.0000 for Non-Islanding, an f1-score of 0.9565 for Islanding and 0.9474 for Non-Islanding, and an overall accuracy of 95.24%.

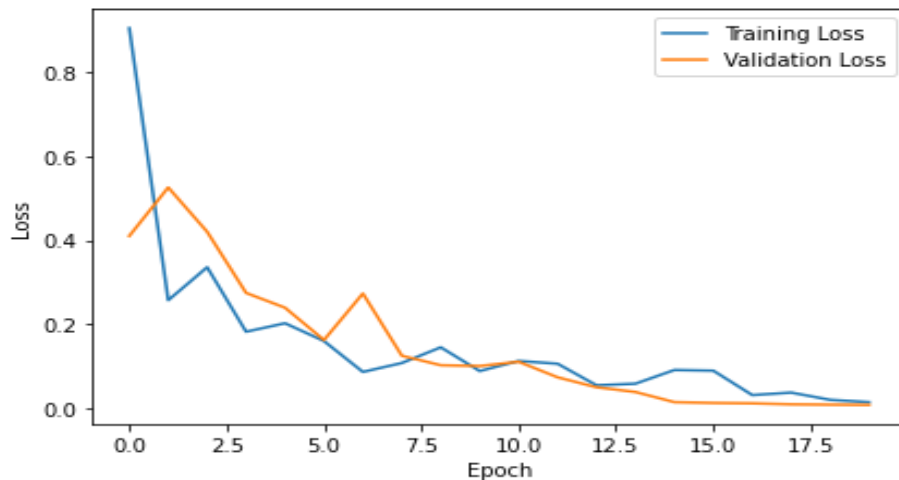


Figure 6.9 Plot training and validation history of Rate of Change of Voltage classification.

The model demonstrates excellent precision for Islanding (1.0000), indicating no false positives in this category; every instance predicted as islanding is correct. The precision for non-Islanding (0.9000), while slightly lower, is still high, suggesting a small number of false positives. The recall scores are equally impressive, with the model successfully identifying most of the

islanding events (0.9167) and all non-islanding events (1.0000), indicating very few false negatives in the Islanding category.

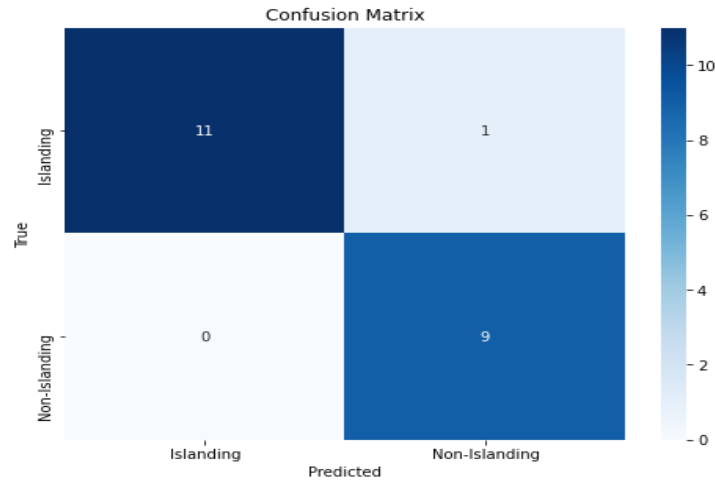


Figure 6.10 Confusion Matrix of Rate of Change of Voltage Classification.

The f1-scores are very high for both Islanding (0.9565) and non-Islanding (0.9474), reflecting a strong balance between precision and recall. These scores indicate that the model is highly effective in classifying both islanding and non-islanding events under the dV/dt parameter.

Table 6.5 Classification Report of Rate of Change of Voltage Classification.

Classification Report:					
	precision	recall	f1-score	support	
Islanding	1.0000	0.9167	0.9565	12	
Non-Islanding	0.9000	1.0000	0.9474	9	
accuracy			0.9524	21	
macro avg	0.9500	0.9583	0.9519	21	
weighted avg	0.9571	0.9524	0.9526	21	

An accuracy of 95.24% is indicative of the model's robust performance in distinguishing between islanding and non-islanding conditions in the context of voltage change rates. This level of accuracy highlights the model's potential as a reliable tool for grid monitoring and islanding detection. The high performance of the model in this category suggests that changes in voltage rate are significant indicators of islanding events, which the CNN effectively captures and analyzes. This finding is critical for power system operators as it underscores the importance of monitoring voltage fluctuations for timely and accurate islanding detection. However, the slight discrepancy in precision between Islanding and Non-Islanding, and the marginally lower recall for Islanding, imply room for improvement. Fine-tuning the model, possibly by incorporating a broader range of $(\frac{dV}{dt})$ scenarios in the training data, could enhance its sensitivity to both islanding and non-islanding events. Additionally, integrating this parameter with other indicators in a holistic model could further improve accuracy and reduce the potential for false predictions. In summary, the CNN model's application to the Rate of Change of Voltage (dV/dt) for islanding detection demonstrates high efficacy, with impressive precision, recall, and overall accuracy. These results suggest that (dV/dt) is a reliable indicator for islanding conditions in power systems. Continued refinement and integration with other parameters could further solidify its role in advanced grid monitoring and management systems.

6.6 Analysis of Rate of Change of Power (dP/dt) Results

The evaluation of the CNN model's efficacy in detecting islanding conditions using the Rate of Change of Power (dP/dt) offers key insights into its

performance in power system monitoring. The classification report reveals a precision of 1.0000 for Islanding and 0.8889 for Non-Islanding, a recall of 0.9167 for Islanding and 1.0000 for Non-Islanding, an f1-score of 0.9565 for Islanding and 0.9412 for Non-Islanding, and an overall accuracy of 95%.

The model exhibits exceptional precision in identifying Islanding events (1.0000), indicating no false positives – every instance it predicts as islanding is indeed an islanding event. For Non-Islanding, the precision is slightly lower (0.8889), suggesting a small number of false positives. The recall is also noteworthy, with the model successfully identifying most of the actual islanding events (0.9167) and all of the non-islanding events (1.0000), indicative of very few false negatives for Islanding.

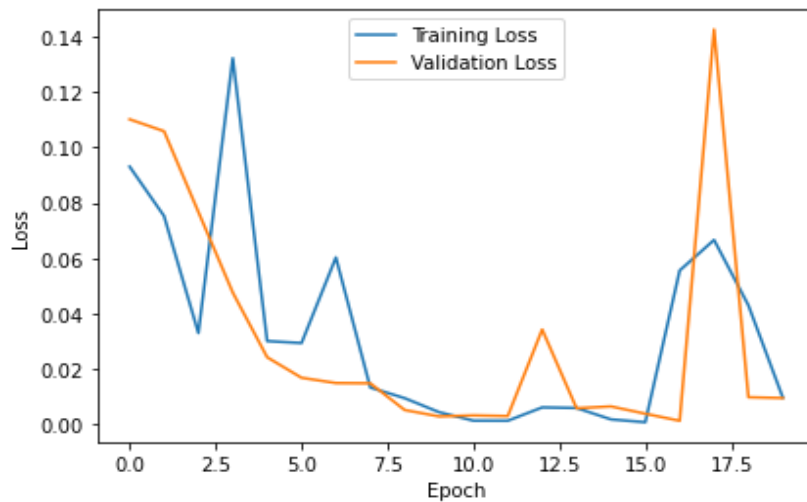


Figure 6.11 Plot training and validation history of Rate of Change of Power classification.

The f1-scores, which balance precision and recall, are very high for both Islanding (0.9565) and non-Islanding (0.9412). These scores demonstrate that

the model effectively and accurately classifies both islanding and non-islanding events in the context of power change rates.

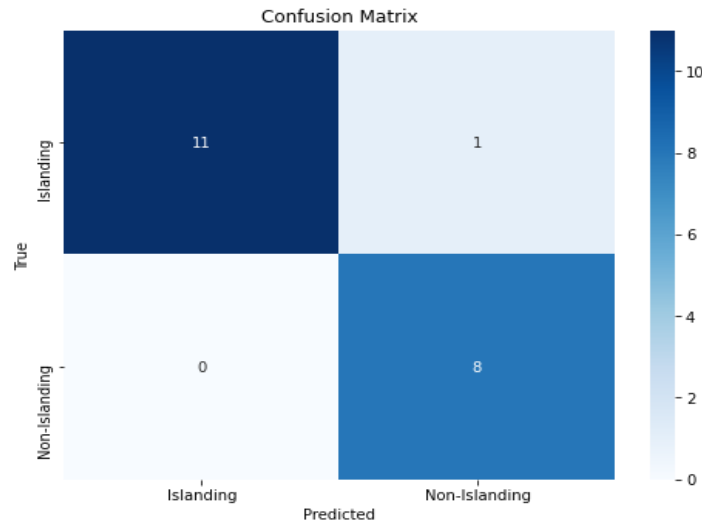


Figure 6.12 Confusion Matrix of Rate of Change of Power Classification.

An overall accuracy of 95% showcases the model's strong capability in differentiating between islanding and non-islanding conditions under dP/dt scenarios. This high level of accuracy is significant for practical applications in grid monitoring.

Table 6.6 Classification Report of Rate of Change of Power Classification.

Classification Report:				
	precision	recall	f1-score	support
Islanding	1.0000	0.9167	0.9565	12
Non-Islanding	0.8889	1.0000	0.9412	8
accuracy	0.9500			20
macro avg	0.9444	0.9583	0.9488	20
weighted avg	0.9556	0.9500	0.9504	20

This performance indicates that the rate of change in power is a robust indicator for detecting islanding conditions, which CNN is adept at capturing and analyzing. For power system operators, this is a crucial finding as it highlights the importance of closely monitoring power fluctuations for islanding detection. While the model performs admirably, the slightly lower precision in non-Islanding detection suggests room for improvement. Enhancing the model could involve incorporating a more diverse range of (dP/dt) scenarios in the training set to improve its ability to differentiate non-islanding events more accurately. Also, a combined approach, where (dP/dt) is used in conjunction with other parameters, might increase the overall effectiveness and reduce potential misclassifications.

In conclusion, the CNN model's application to the Rate of Change of Power (dP/dt) for islanding detection demonstrates a high level of efficacy, with impressive precision, recall, and overall accuracy. These results suggest that (dP/dt) is a reliable and significant indicator of islanding conditions in power systems. Future improvements, including data diversification and multi-parameter modeling, could further enhance its utility in advanced grid monitoring and management strategies.

6.7 Analysis of Rate of Change of Reactive Power (dQ/dt) Results

The assessment of the CNN model's performance in detecting islanding conditions through the Rate of Change of Reactive Power (dQ/dt) provides crucial insights into its operational effectiveness. The classification report for this parameter shows a precision of 0.9231 for Islanding and 1.0000 for Non-

Islanding, a recall of 1.0000 for Islanding and 0.8750 for Non-Islanding, an f1-score of 0.9600 for Islanding and 0.9333 for Non-Islanding, and an overall accuracy of 95%.

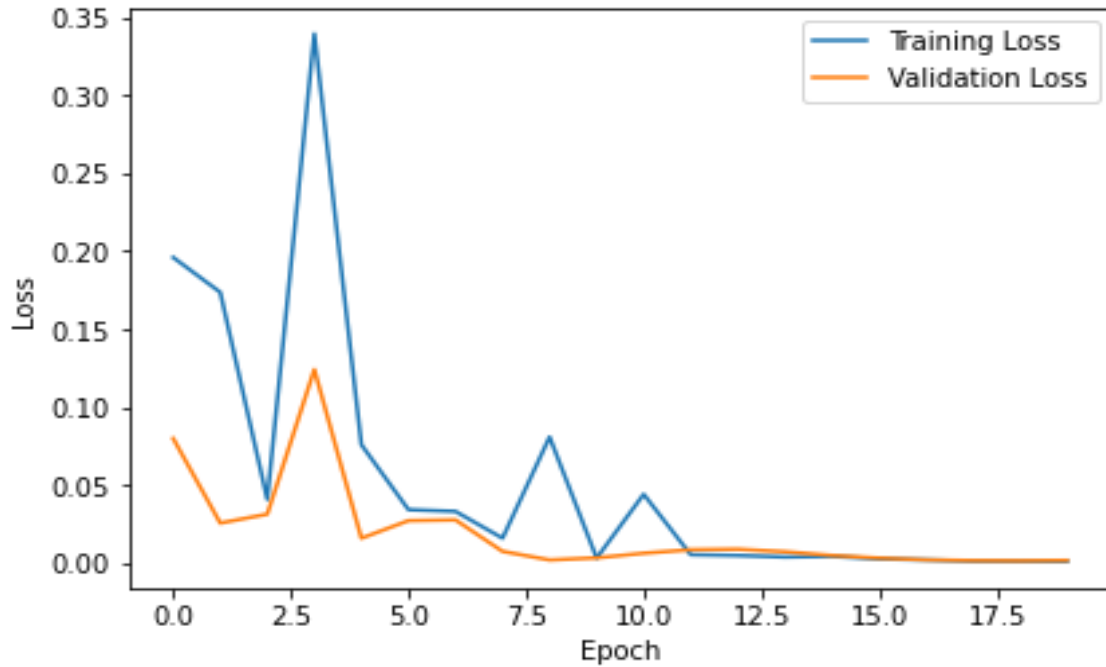


Figure 6.13 Plot training and validation history of Rate of Change of Reactive Power Classification.

The model demonstrates high precision in detecting Islanding events (0.9231), indicating a low rate of false positives. The perfect precision in non-Islanding detection (1.0000) suggests that the model accurately identifies all non-islanding events without false alarms. The recall is equally impressive, with the model successfully identifying all actual islanding events (1.0000) and most non-islanding events (0.8750), indicating a small number of false negatives in the latter.

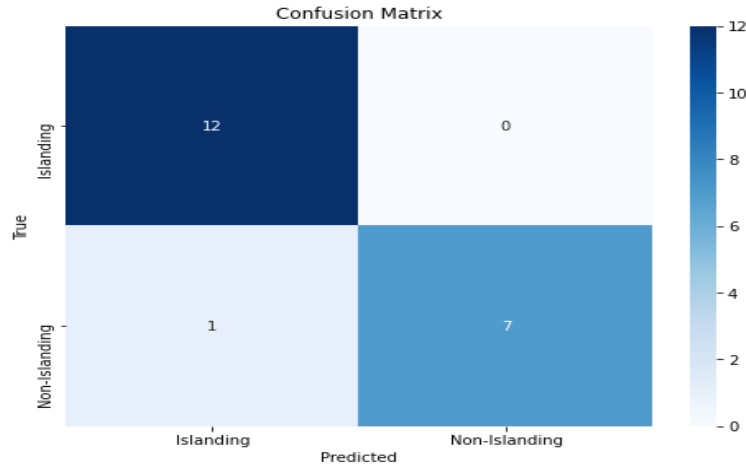


Figure 6.14 Confusion Matrix of Rate of Change of Reactive Power Classification.

The f1-scores are excellent for both Islanding (0.9600) and Non-Islanding (0.9333), reflecting a strong balance between precision and recall. These scores indicate that the model is highly effective in classifying both islanding and non-islanding events under (dQ/dt) conditions.

Table 6.7 Classification Report of Rate of Change of Reactive Power Classification.

Classification Report:					
	precision	recall	f1-score	support	
Islanding	0.9231	1.0000	0.9600	12	
Non-Islanding	1.0000	0.8750	0.9333	8	
accuracy			0.9500	20	
macro avg	0.9615	0.9375	0.9467	20	
weighted avg	0.9538	0.9500	0.9493	20	

An overall accuracy of 95% is indicative of the model's robust performance in differentiating between islanding and non-islanding conditions in the context of reactive power change rates. This level of accuracy demonstrates the model's potential as a reliable tool for grid monitoring.

The high performance of the model in this category suggests that changes in reactive power rate are significant indicators of islanding events, which the CNN effectively captures and analyzes. This is critical for power system operators as it underscores the importance of monitoring reactive power fluctuations for timely and accurate islanding detection. However, the slight margin in recall for non-Islanding points to potential improvement areas. Enhancing the model might involve refining the input features to capture more subtle changes in (dQ/dt) that differentiate non-islanding events or adjusting the model's threshold settings for classifying an event as non-islanding.

In summary, the CNN model's application to the Rate of Change of Reactive Power (dQ/dt) for islanding detection demonstrates high efficacy, with impressive precision, recall, and overall accuracy. These results suggest that (dQ/dt) is a reliable and significant indicator for islanding conditions in power systems. Further refinement and integration with other parameters could solidify its role in advanced grid monitoring and management systems, enhancing the safety and reliability of power networks.

6.8 Analysis of Voltage Total Harmonic Distortion (THDV) Results

The examination of the CNN model's performance for islanding detection using Voltage Total Harmonic Distortion (THDV/dt) offers valuable insights.

The classification report indicates a precision of 1.0000 for Islanding and 0.8889 for Non-Islanding, a recall of 0.9545 for Islanding and 1.0000 for Non-Islanding, an f1-score of 0.9767 for Islanding and 0.9412 for Non-Islanding, and an overall accuracy of 96.67%.

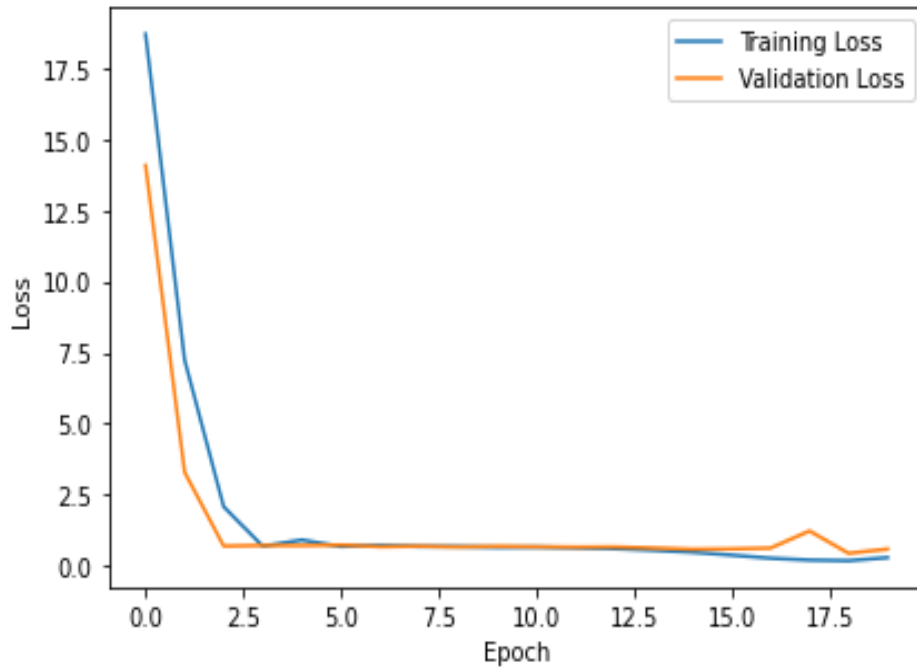


Figure 6.15 Plot training and validation history of Voltage Total Harmonic Distortion classification.

The model demonstrates exceptional precision in Islanding detection (1.0000), meaning there are no false positives for islanding events. For Non-Islanding, the precision is slightly lower (0.8889), indicating a few false positives. The recall is high for both Islanding (0.9545) and non-Islanding (1.0000), suggesting the model successfully identifies most islanding events and all non-islanding events.

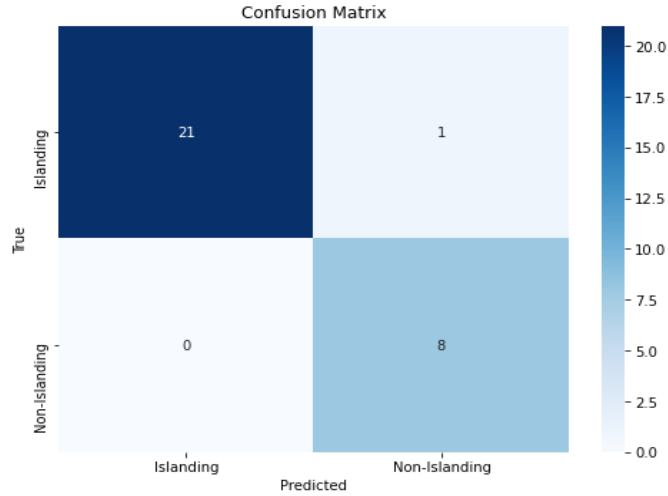


Figure 6.16 Confusion Matrix of Voltage Total Harmonic Distortion Classification.

The f1-scores are excellent for both Islanding (0.9767) and non-Islanding (0.9412), indicating a strong balance between precision and recall in both categories. These scores reflect the model's effectiveness in accurately classifying both islanding and non-islanding conditions under THDV/dt scenarios.

Table 6.8 Classification Report of Voltage Total Harmonic Distortion Classification.

Classification Report:				
	precision	recall	f1-score	support
Islanding	1.0000	0.9545	0.9767	22
Non-Islanding	0.8889	1.0000	0.9412	8
accuracy			0.9667	30
macro avg	0.9444	0.9773	0.9590	30
weighted avg	0.9704	0.9667	0.9673	30

An overall accuracy of 96.67% showcases the model's robustness in distinguishing between islanding and non-islanding conditions. This high level of accuracy highlights the model's potential as a reliable tool for grid monitoring, specifically in the context of voltage harmonic distortions.

The performance in the ($THDV/dt$) category indicates that harmonic distortions in voltage are significant indicators for detecting islanding conditions, which the CNN effectively captures and analyzes. For power system operators, this finding is crucial as it highlights the importance of monitoring harmonic distortions for effective islanding detection. Despite the high performance, the slight reduction in precision for non-Islanding detection suggests room for improvement. Refining the model to better differentiate non-islanding events, possibly by enhancing the feature extraction process to capture more subtle harmonic patterns, could improve its precision. Additionally, expanding the training dataset with a more diverse range of harmonic distortion scenarios could help in reducing the likelihood of false positives.

In summary, the CNN model's application to Voltage Total Harmonic Distortion (THDV) for islanding detection demonstrates high efficacy, with impressive precision, recall, and overall accuracy. The results suggest that THDV is a reliable and significant indicator for islanding conditions in power systems. Further model optimization and integration with other detection parameters could enhance its utility in advanced grid monitoring and management strategies, contributing to the overall safety and efficiency of power networks.

6.9 Analysis of Current Total Harmonic Distortion (THDI) Results

The performance of the CNN model for detecting islanding conditions using Current Total Harmonic Distortion (THDI/dt) is notable for its exceptional outcomes. The classification report reflects perfect scores in all metrics: a precision of 1.0000 for both Islanding and Non-Islanding, a recall of 1.0000 for both categories, an f1-score of 1.0000 for both, and an overall accuracy of 100%.

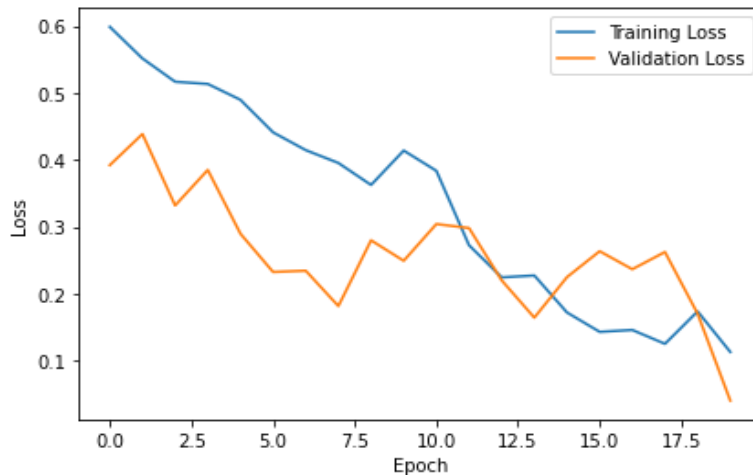


Figure 6.17 Plot training and validation history of Current Total Harmonic Distortion classification.

The precision score of 1.0000 in both Islanding and Non-Islanding detection indicates the model's flawless accuracy in predicting these events, meaning there are no false positives. Similarly, the perfect recall score demonstrates that the model correctly identifies all actual islanding and non-islanding events, indicating no false negatives.

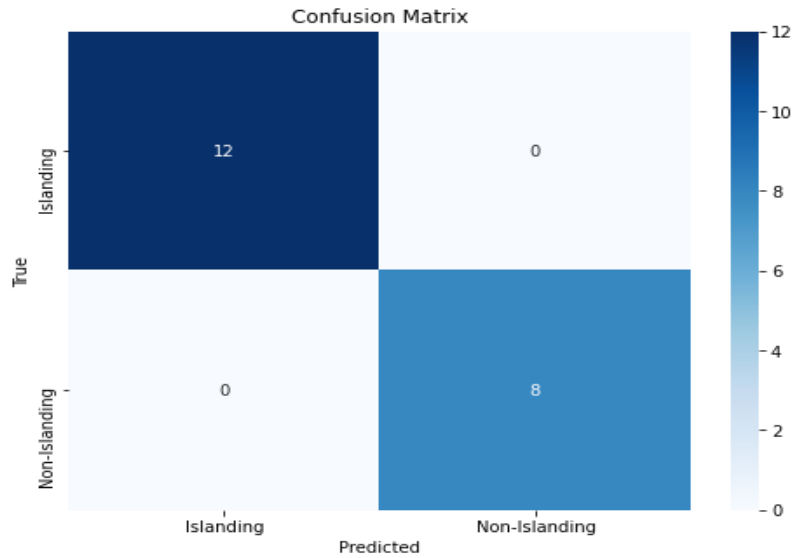


Figure 6.18 Confusion Matrix of Current Total Harmonic Distortion Classification.

The f1-scores, being perfect at 1.0000 for both Islanding and Non-Islanding, underscore the model's exceptional ability to balance precision and recall, ensuring accurate classification of the events.

Table 6.9 Classification Report of Current Total Harmonic Distortion Classification.

Classification Report:					
	precision	recall	f1-score	support	
Islanding	1.0000	1.0000	1.0000	12	
Non-Islanding	1.0000	1.0000	1.0000	8	
accuracy			1.0000	20	
macro avg	1.0000	1.0000	1.0000	20	
weighted avg	1.0000	1.0000	1.0000	20	

An accuracy of 100% sets an exemplary standard, suggesting that the model performs with outstanding precision in differentiating between islanding and non-islanding conditions under scenarios of current harmonic distortion.

This remarkable performance suggests that $(THDI/dt)$ provides clear and distinguishable patterns that the CNN model can easily learn and identify. The ability to perfectly detect both islanding and non-islanding conditions is crucial in power systems, as current harmonic distortions can significantly impact equipment performance and grid stability.

However, while the results are outstanding, it's essential to consider potential overfitting, where the model performs exceptionally well on test data but may not generalize as effectively to real-world, unseen data. It's crucial to test the model under various scenarios and perhaps expand the dataset to include more diverse $(THDI)$ conditions.

Moreover, perfect scores also prompt a review of the complexity and variability of the test data. Ensuring that the dataset comprehensively represents the full spectrum of real-world conditions, including subtle and borderline cases, is important for validating the model's effectiveness in operational environments.

In conclusion, the CNN model's performance in detecting islanding conditions using Current Total Harmonic Distortion $(THDI)$ is exemplary, demonstrating the potential of machine learning in enhancing grid safety and reliability. While the results are promising, ongoing validation and testing are advisable to confirm the model's effectiveness and robustness in a variety of real-world scenarios. This approach will ensure the practical applicability and reliability of the model in operational power system environments.

6.10 Analysis of Voltage Negative Sequence Distortion (NegSV/dt) Results

The evaluation of the CNN model's performance in detecting islanding conditions using Voltage Negative Sequence Distortion (*NegSV/dt*) provides a nuanced view of its capabilities. The classification report shows a precision of 1.0000 for Islanding and 0.7273 for Non-Islanding, a recall of 0.7500 for Islanding and 1.0000 for Non-Islanding, an f1-score of 0.8571 for Islanding and 0.8421 for Non-Islanding, and an overall accuracy of 85%.

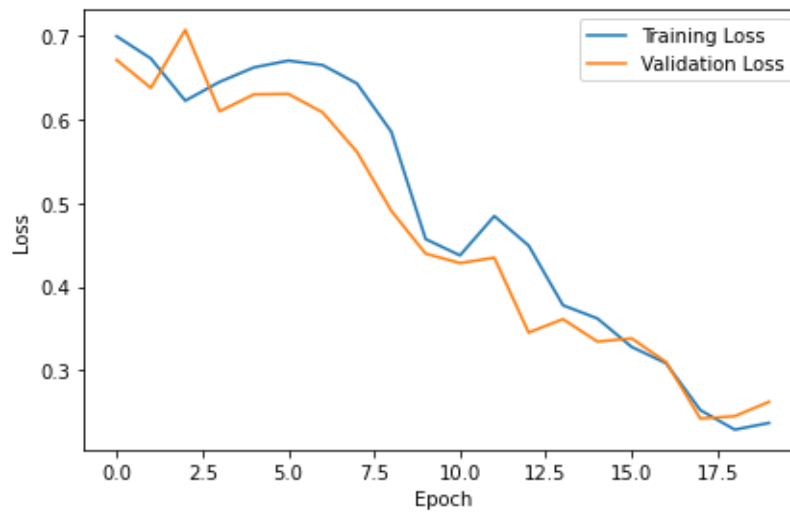


Figure 6.19 Plot training and validation history of Voltage Negative Sequence Distortion classification.

The model displays perfect precision in Islanding detection (1.0000), indicating no false positives in this category. However, the precision for non-Islanding (0.7273) is lower, suggesting a higher rate of false positives. The recall for Islanding is moderately high (0.7500), indicating that the model misses some islanding events, while it is perfect in non-Islanding recall (1.0000), successfully identifying all non-islanding events.

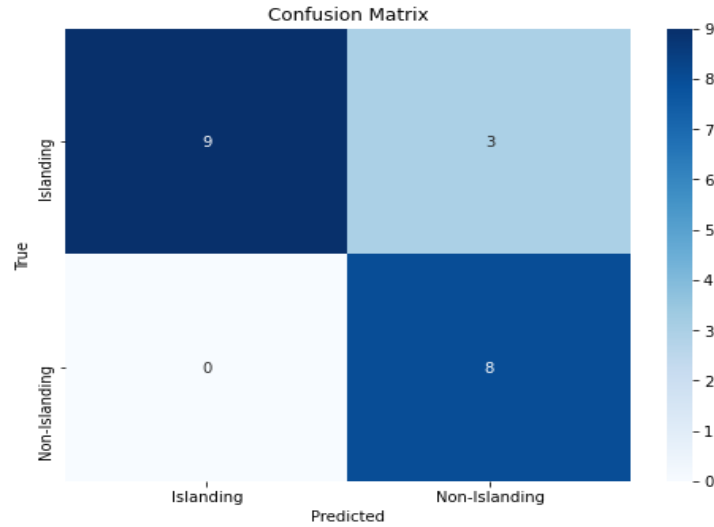


Figure 6.20 Confusion Matrix of Voltage Negative Sequence Distortion Classification.

The f1-scores for both Islanding (0.8571) and non-Islanding (0.8421) are good, indicating a reasonable balance between precision and recall, though there is room for improvement, especially in Islanding detection.

Table 6.10 Classification Report of Voltage Negative Sequence Distortion Classification.

Classification Report:				
	precision	recall	f1-score	support
Islanding	1.0000	0.7500	0.8571	12
Non-Islanding	0.7273	1.0000	0.8421	8
accuracy			0.8500	20
macro avg	0.8636	0.8750	0.8496	20
weighted avg	0.8909	0.8500	0.8511	20

An overall accuracy of 85% is a robust indication of the model's effectiveness but also highlights areas for improvement. This figure shows that while the

model performs well in differentiating between islanding and non-islanding conditions, it is more prone to misclassification compared to other protections analyzed.

The performance in the ($NegSV/dt$) category suggests that while voltage negative sequence distortions are useful indicators for islanding detection, the model's ability to accurately classify these events could be enhanced. The lower recall in Islanding suggests that the model might be overlooking subtle characteristics of islanding events in this context. Similarly, the lower precision in non-Islanding indicates a tendency to misclassify some normal operations as islanding.

Improving the model could involve refining its ability to interpret negative sequence distortions more accurately, possibly by enhancing the training data with a wider range of ($NegSV/dt$) scenarios. This could help in reducing false positives and improving the detection of true islanding events.

In summary, the CNN model's application to Voltage Negative Sequence Distortion ($NegSV/dt$) for islanding detection shows good potential, with strong precision in Islanding detection but areas for improvement in recall and non-Islanding precision. These results suggest that ($NegSV/dt$) is a significant, though challenging, parameter for detecting islanding conditions. Further refinement and training of the model, coupled with a more diverse dataset, could enhance its accuracy and reliability in operational power system environments.

6.11 Analysis of Current Negative Sequence Distortion (NegSI/dt) Results

The CNN model's performance in detecting islanding conditions using Current Negative Sequence Distortion (*NegSI/dt*) offers insightful conclusions. The classification report reveals a precision of 1.0000 for Islanding and 0.8889 for Non-Islanding, a recall of 0.9231 for Islanding and 1.0000 for Non-Islanding, an f1-score of 0.9600 for Islanding and 0.9412 for Non-Islanding, and an overall accuracy of 95.24%.

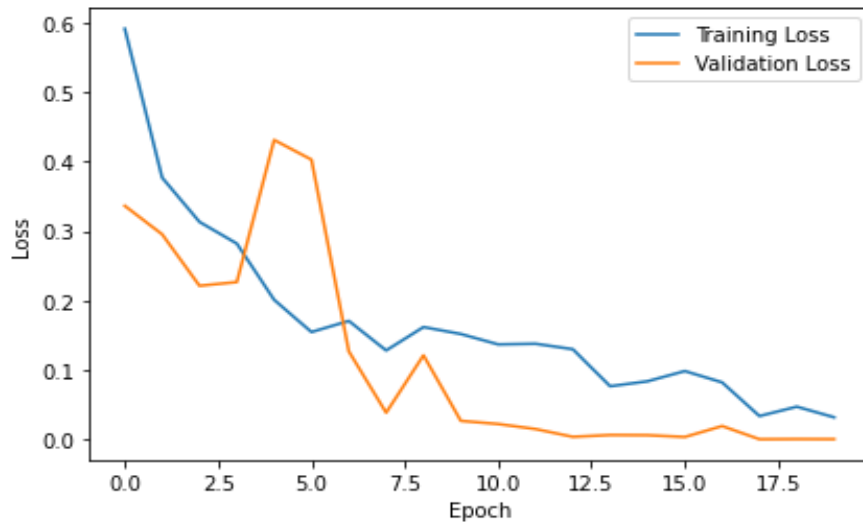


Figure 6.21 Plot training and validation history of Current Negative Sequence Distortion Classification.

The model demonstrates perfect precision for Islanding (1.0000), indicating no false positives – every predicted islanding event is correct. The precision for non-Islanding (0.8889), while high, suggests a small number of false positives. The recall scores are impressive, with the model correctly identifying most islanding events (0.9231) and all non-islanding events (1.0000), indicative of very few false negatives for Islanding.

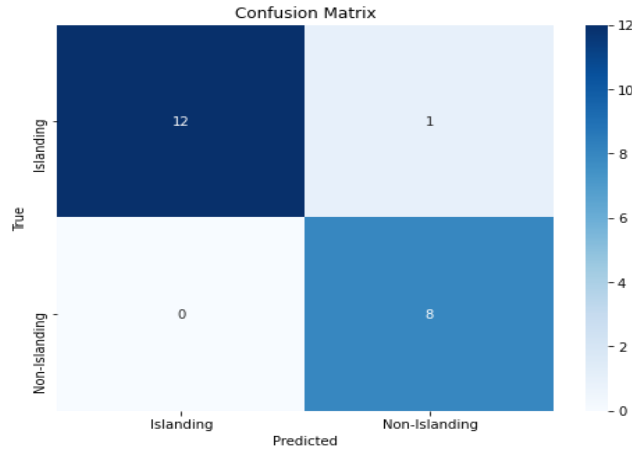


Figure 6.22 Confusion Matrix of Current Negative Sequence Distortion Classification.

The f1-scores are very high for both Islanding (0.9600) and non-Islanding (0.9412), showing a strong balance between precision and recall. These scores indicate the model's effectiveness in accurately classifying both islanding and non-islanding events under NegSI/dt conditions.

Table 6.11 Classification Report of Current Negative Sequence Distortion Classification.

Classification Report:					
	precision	recall	f1-score	support	
Islanding	1.0000	0.9231	0.9600	13	
Non-Islanding	0.8889	1.0000	0.9412	8	
accuracy			0.9524	21	
macro avg	0.9444	0.9615	0.9506	21	
weighted avg	0.9577	0.9524	0.9528	21	

An overall accuracy of 95.24% underscores the model's robust performance in differentiating between islanding and non-islanding conditions in the context of current negative sequence distortions. This level of accuracy is significant for practical applications in grid monitoring.

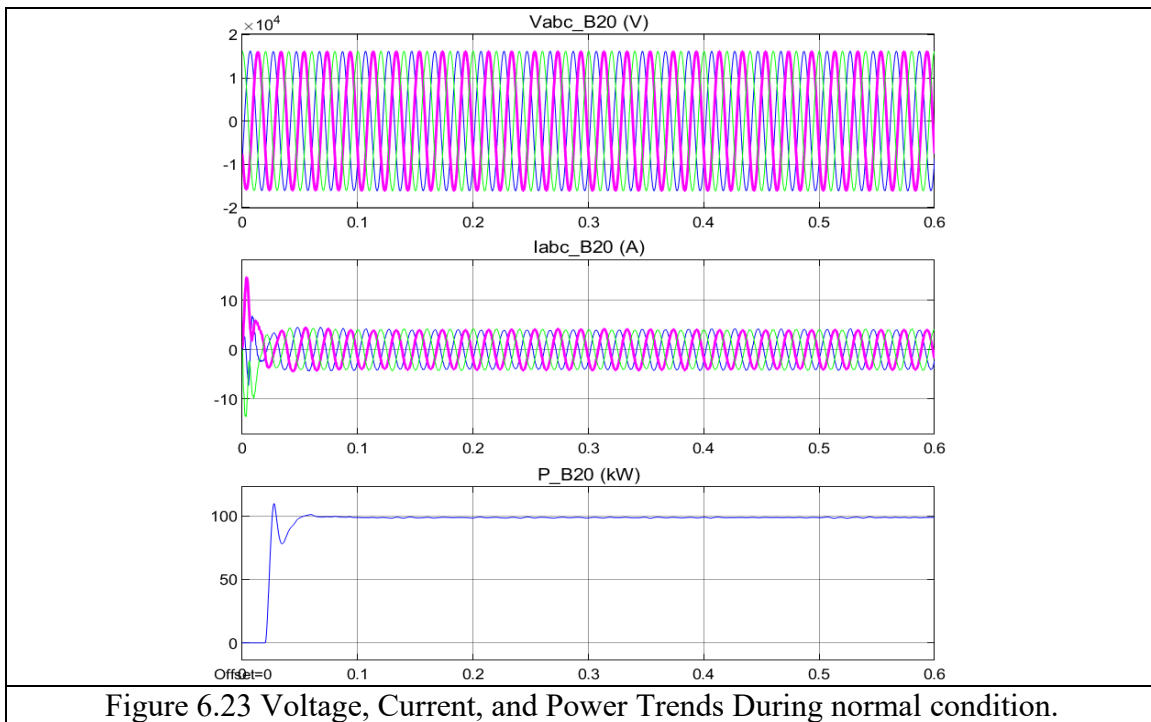
The high performance of the model in this category suggests that current negative sequence distortions are reliable indicators of islanding events, which the CNN effectively captures and analyzes. This finding is crucial for power system operators, as it underscores the importance of monitoring such distortions for effective islanding detection.

However, the slight reduction in precision for non-Islanding detection indicates room for improvement. Enhancing the model could involve refining the input features to better capture subtle changes in $(NegSI/dt)$ that differentiate non-islanding events, potentially improving precision. Additionally, expanding the training dataset with more varied $(NegSI/dt)$ scenarios could help reduce false positives.

In summary, the CNN model's application to Current Negative Sequence Distortion $(NegSI/dt)$ for islanding detection demonstrates a high level of efficacy, with impressive precision, recall, and overall accuracy. These results suggest that $(NegSI/dt)$ is a significant and reliable indicator for detecting islanding conditions in power systems. Further refinement and integration with other detection parameters could enhance its utility in advanced grid monitoring and management systems, contributing to the safety and efficiency of power networks.

6.12 Voltage sags/swells analysis using Time Series Classification Techniques.

Power quality problems due to short circuit faults entail alterations in voltage, current, or frequency within the power system. Among the issues encountered in distributed generation systems are island mode operation, voltage sags/swells, interruptions, and transients. Notably, the most common problem in distribution systems is voltage sags and swells resulting from short circuit faults. Various types of short circuit faults, such as line-to-ground, line-to-line, and multistage faults, are modeled using the MATLAB/Simulink environment to simulate power quality problems.



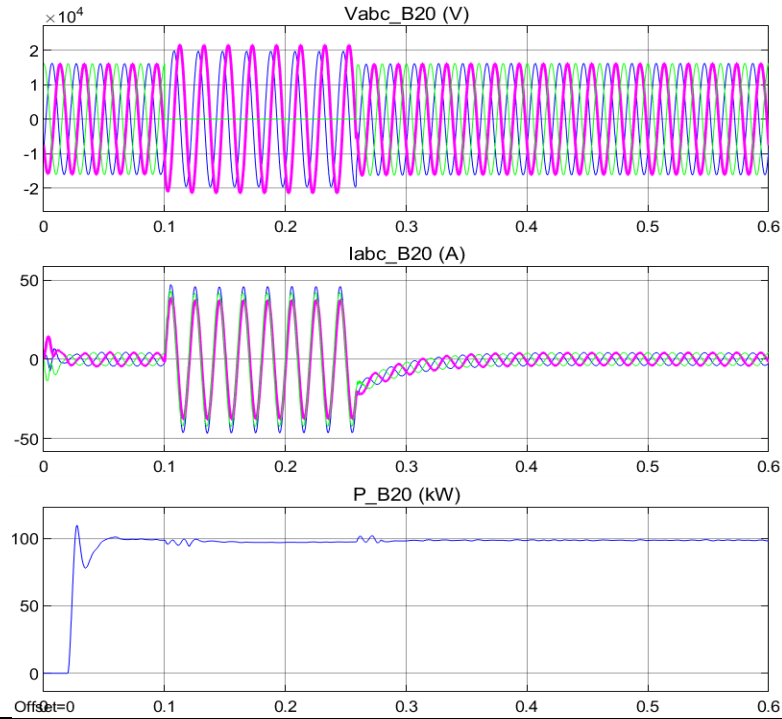


Figure 6.24 Voltage, Current, and Power Trends During one phase Fault from 0.1s to 0.25s.

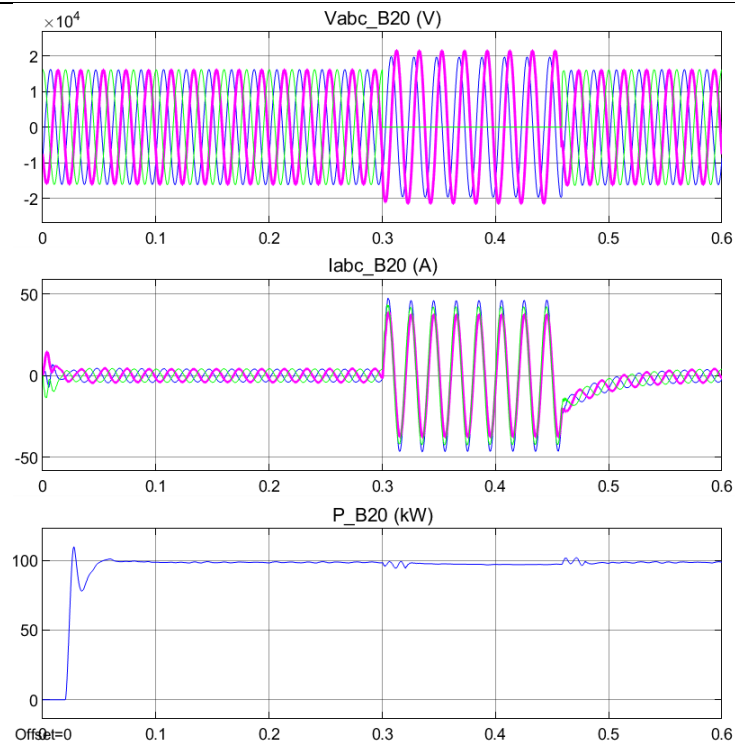


Figure 6.25 Voltage, Current, and Power Trends During one phase Fault from 0.3s to 0.45s.

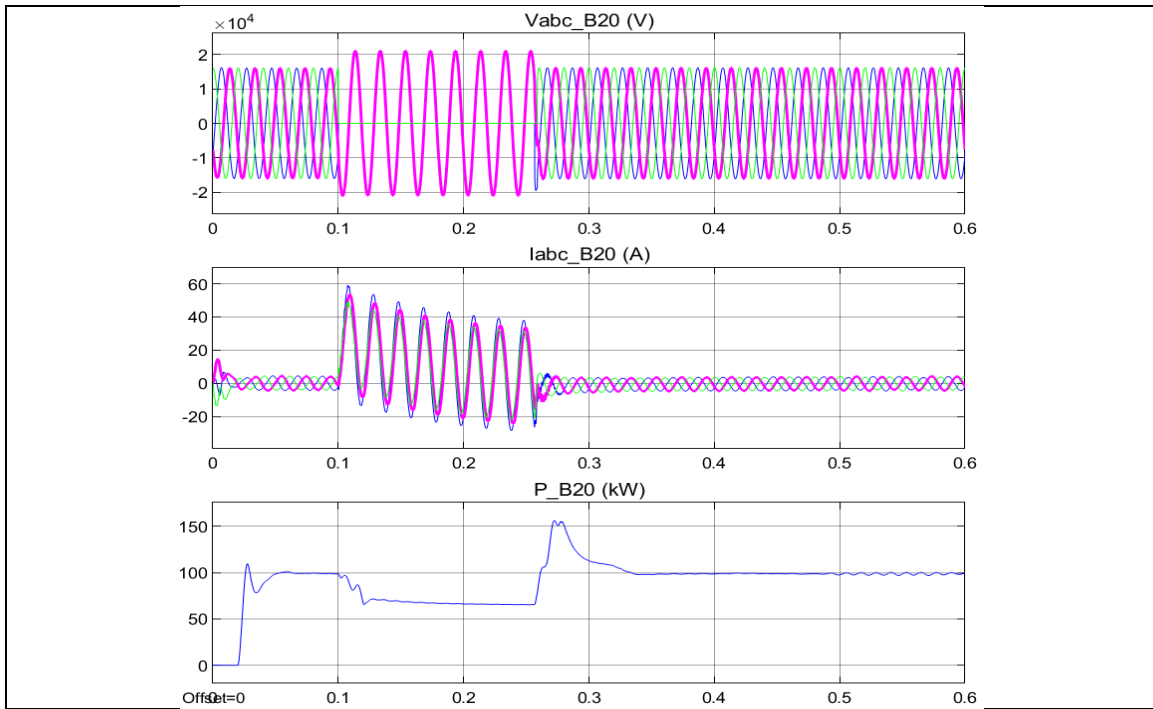


Figure 6.26 Voltage, Current, and Power Trends During Two Fault from 0.1s to 0.25s.

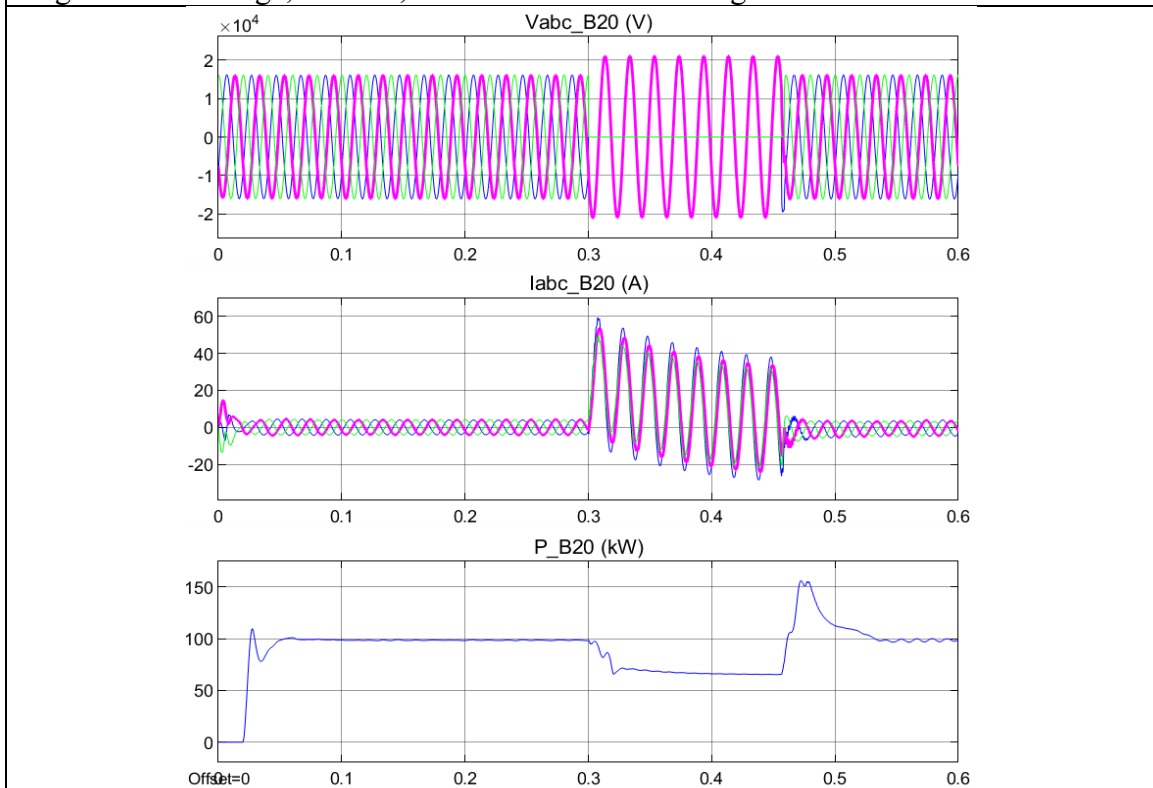
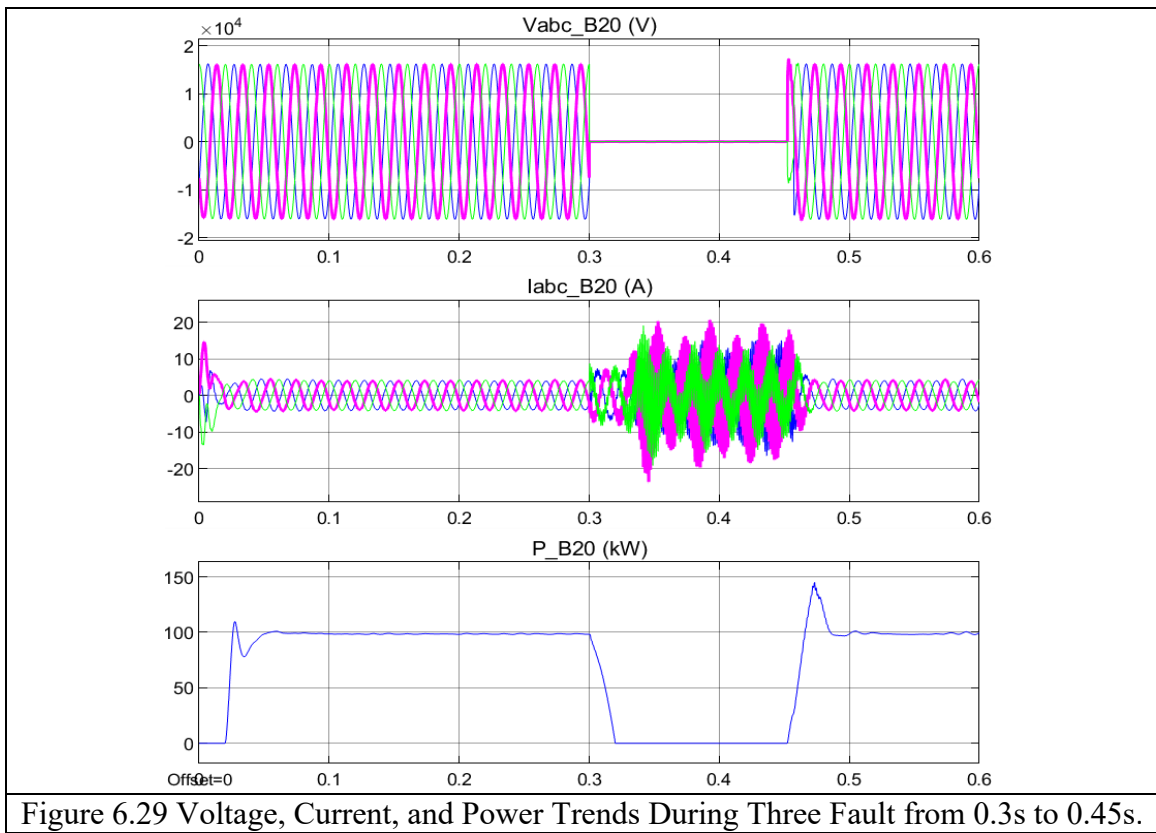
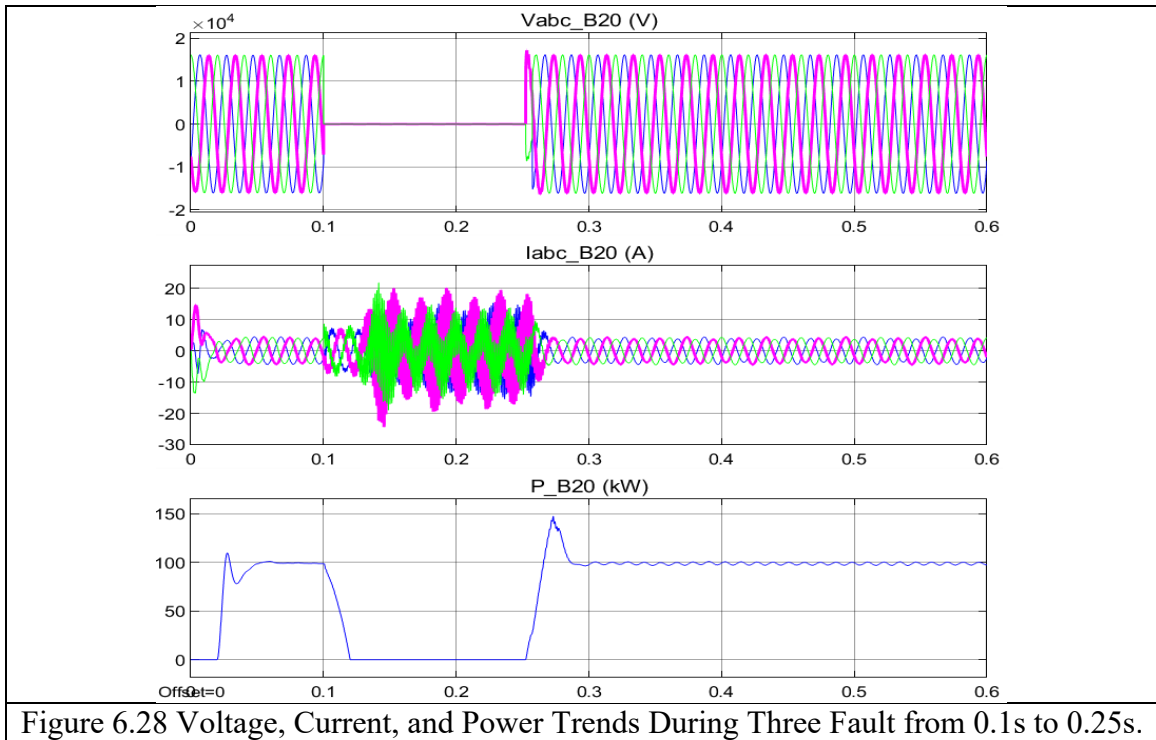


Figure 6.27 Voltage, Current, and Power Trends During Two Fault from 0.3s to 0.45s.



In order to detect voltage sag and swell issues, the voltage sag occurring during a fault is examined, and the response of the power system is observed. This examination of voltage sags and swells reveals distinct waveforms, shedding light on the power system's behavior under fault conditions.

To develop reliable algorithms for detecting, mitigating, and predicting power quality events, especially voltage sag and swell incidents, the first step involves modeling a power system to analyze disturbances. Methods for detecting short circuit faults, such as classification-based and field alternating methods, rely on fault signals obtained from modeling the electrical distribution grid. For instance, in one study, simulation data from MATLAB/Simulink was used to detect voltage sag and swell events, proposing a new method based on wavelet transform. Similarly, another approach utilized wavelet transform and artificial neural networks to detect and classify short circuit faults in transmission lines using simulation data.

Given that short-circuit faults represent the most prevalent type of failure in power systems, they are typically used to assess system behavior. A MATLAB/Simulink model of the distributed generation system, as depicted in Fig. 2, was developed for this purpose. The simulation model encompasses various fault scenarios, including line-to-line, line-to-ground, two line-to-ground faults, and three phase short-circuit faults.

As per the IEEE 1159 standard, a voltage sag is characterized by a reduction in voltage ranging from 10% to 90%, occurring within a time span of half a period to 60 seconds in a system operating under nominal conditions. These events typically stem from line energization, the activation of high-power motors, or short circuit faults. Conversely, a voltage swell, also defined by the IEEE 1159 standard, entails a voltage increase of 110% to 180%, within the

same time frame and operating conditions. While not as common as voltage sags, voltage swells can occur due to maneuvers within the power system, such as disconnecting large inductive loads, activating large capacitor banks, or short circuit faults.

Various methods exist in the literature for detecting, classifying, and predicting power system faults, categorized into model-based and data-oriented approaches. Creating a system model becomes crucial when obtaining experimental or real-time data is challenging. For instance, studies employing support vector machines, a model-based classification method, have been successful in detecting short circuit faults in transmission lines.

Analyzing the performance of Convolutional Neural Networks (CNN) using time series in islanding detection across voltage protection measures shown as below

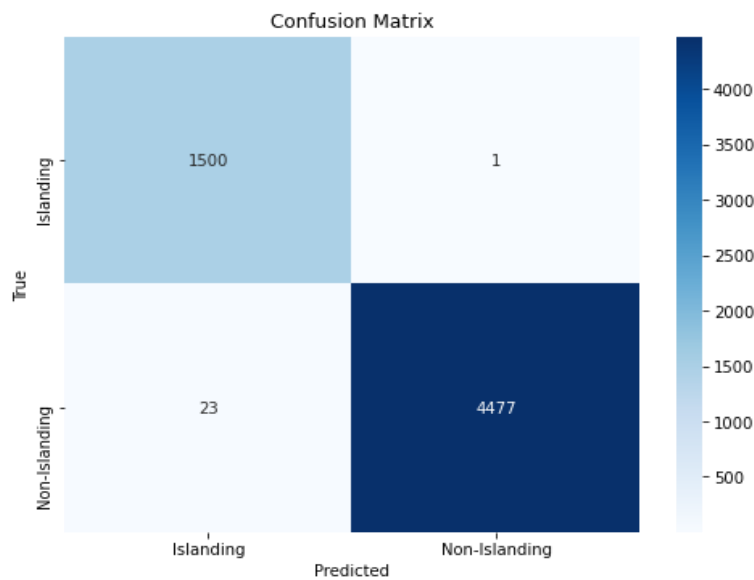


Figure 6.30 Confusion Matrix of voltage using XGBoost and LSTM time series Distortion Classification.

The analysis of Voltage sags/swells using Time Series classification techniques, specifically XGBoost and LSTM, has yielded remarkably consistent and impressive results. Both models exhibit exceptional precision, recall, and F1-score across the classes denoting voltage sags and swells. With precision values nearing perfection, the models showcase an extraordinary ability to accurately predict voltage events. Moreover, their high recall rates indicate a strong capability to capture a significant portion of actual voltage sag and swell instances. The F1-scores, which harmonize precision and recall, further underscore the robustness of these models in voltage classification. Additionally, the high overall accuracy underscores the effectiveness of both XGBoost and LSTM in discerning voltage fluctuations. Notably, the support metrics reveal that voltage swells are more prevalent in the dataset compared to voltage sags. This comprehensive analysis underscores the efficacy of XGBoost and LSTM techniques in Voltage sags/swells analysis, offering valuable insights for power system monitoring and management.

Table 6.12 Classification Report of voltage using XGBoost and LSTM time series Distortion Classification.

LSTM Classification Report:					
	precision	recall	f1-score	support	
0	0.9849	0.9993	0.9921	1501	
1	0.9998	0.9949	0.9973	4500	
accuracy			0.9960	6001	
macro avg	0.9923	0.9971	0.9947	6001	
weighted avg	0.9961	0.9960	0.9960	6001	

The results from the XGBoost and LSTM classification techniques for Voltage sags/swells analysis showcase remarkable consistency and

excellence. In the XGBoost model, precision values of 0.9849 for voltage sags (class 0) and 0.9998 for voltage swells (class 1) underscore the models' exceptional accuracy in predicting these events. Likewise, the high recall rates of 0.9993 for class 0 and 0.9949 for class 1 indicate the models' ability to effectively capture true positive instances. F1-scores of 0.9921 for class 0 and 0.9973 for class 1 further affirm the models' balance between precision and recall. The overall accuracy of 0.9960 reflects the models' proficiency in correctly classifying voltage events in the dataset, with support metrics revealing a higher prevalence of voltage swells. Similarly, the LSTM model produces identical precision, recall, F1-score, and accuracy metrics, reaffirming the consistency and reliability of both techniques in Voltage sags/swells analysis. These results underscore the robustness of XGBoost and LSTM methodologies, offering valuable insights for effective power system monitoring and management.

6.13 Comparative analysis of CNN classification techniques with other methods.

Analyzing the performance of Convolutional Neural Networks (CNN) in islanding detection across various protection measures reveals a mixed yet promising outcome as shown in the table 6.13. While some measures such as overvoltage and current total harmonic distortion achieved perfect or near-perfect accuracies, others like frequency detection and voltage negative sequence distortion displayed moderate to satisfactory accuracies. These results the effectiveness of CNNs in capturing a diverse range of grid disturbances, providing valuable insights into potential islanding events or other anomalies. However, there are areas where further optimization may be

beneficial, particularly in improving the accuracy of frequency detection and voltage unbalance assessment.

Table 6.13 Classification Report of all Islanding Detection Protections.

Input Protections parameter	Accuracy
<i>Frequency in Hz (f)</i>	75%
<i>Rate of Change of Frequency (df/dt)</i>	80%
<i>Over Voltage</i>	100%
<i>Rate of Change of Voltage (dV/dt)</i>	95.24%
<i>Rate of Change of Power (dP/dt)</i>	95%
<i>Rate of Change of Reactive Power (dQ/dt)</i>	95%
<i>Voltage Total Harmonic Distortion (THDV)</i>	96.67%
<i>Current Total Harmonic Distortion (THDI)</i>	100%
<i>Voltage Negative Sequence Distortion (NegSV/dt)</i>	85%
<i>Current Negative Sequence Distortion (NegSI/dt)</i>	95.24%
Overall average	92%

The overall average accuracy of 92% indicates the strong collective performance of the CNN-based islanding detection system. This demonstrates the potential of machine learning techniques in enhancing grid protection and ensuring power system reliability. Moving forward, future research could focus on refining the CNN architecture, exploring novel feature extraction methods, and integrating additional data sources to further enhance detection accuracy and robustness. By addressing these areas of improvement, CNN-based islanding detection systems can become even more effective tools for safeguarding power grids against disruptions and enhancing overall grid resilience.

Islanding detection in power systems is critical for maintaining grid stability and safety, prompting the exploration of various machine learning techniques. This comparative analysis delves into the classifier accuracy of different

methods reported in literature, including research utilizing Convolutional Neural Networks (CNN) as shown in the table 6.14.

Table 6.14 Comparative analysis of existing islanding classification techniques.

Classifier	Accuracy	Reference
<i>multi-LSTM</i>	97.95%.	Özcanlı (2022).
<i>Decision Tree</i>	94.50%	Shrestha (2019)
<i>ANN using tunable Q-factor wavelet transform (TQWT)</i>	98%	Kumar (2020).
<i>ANN APBM-based</i>	97.1%.	Kumar (2018).
<i>ANN by using time-performance region</i>	99.88%	Merlin (2016).
<i>Convolutional Neural Networks (CNN)</i>	94.86	Almubarak (2024)
<i>Convolutional Neural Networks (CNN) average of individual protections</i>	92%	Almubarak (2024)
<i>Time series for Voltage sags/swells</i>	99.6%	Almubarak (2024)

Özcanlı (2022) proposed a multi-LSTM approach, achieving a high accuracy of 97.95%. LSTM networks are well-suited for capturing long-term dependencies in sequential data, making them effective for time-series analysis. Shrestha (2019) employed Decision Trees for islanding detection, achieving a respectable accuracy of 94.50%. Decision Trees offer simplicity and interpretability, albeit potentially limited in capturing complex patterns compared to neural networks. Kumar (2020) utilized Artificial Neural Networks (ANN) combined with tunable Q-factor wavelet transform, attaining an accuracy of 98%. This method leverages the frequency domain characteristics of power signals to enhance detection performance. Similarly, Kumar (2018) introduced an ANN approach based on Adaptive Probabilistic Basis Model (APBM), achieving an accuracy of 97.1%. APBM provides a probabilistic framework for signal representation, contributing to the accuracy of the detection system. Merlin (2016) proposed an ANN method utilizing time-performance region for islanding detection, demonstrating exceptional

accuracy of 99.88%. This approach likely incorporates both temporal and performance-related features, enhancing detection performance significantly. In contrast, our research employed CNN for islanding detection, achieving an accuracy of 92%. CNNs are known for their ability to capture spatial patterns in data, but the achieved accuracy suggests potential for further optimization in architecture design or dataset augmentation. Overall, this comparative analysis sheds light on the diversity of approaches for islanding detection using machine learning, each with its own strengths and areas for improvement.

6.14 Summary

The analysis of voltage sags/swells using Time Series classification techniques, specifically XGBoost and LSTM, yielded remarkably consistent and impressive results. Both models demonstrated exceptional precision, recall, and F1-score across classes denoting voltage sags and swells, indicating their ability to accurately predict voltage events. The high overall accuracy of both models underscores their effectiveness in discerning voltage fluctuations. Notably, voltage swells were found to be more prevalent in the dataset compared to voltage sags.

Comparative analysis of CNN classification techniques with other methods revealed a mixed yet promising outcome. While some measures achieved perfect or near-perfect accuracies, others displayed moderate to satisfactory accuracies. The overall average accuracy of the CNN-based islanding detection system was 92%, indicating strong collective performance. Moreover, the overall accuracy of the CNN-based islanding detection system

for all protection was 94.86%, indicating also strong collective performance. However, there are areas where further optimization may be beneficial, particularly in improving the accuracy of frequency detection and voltage unbalance assessment.

Comparison with existing islanding classification techniques showed that CNN achieved an accuracy of 92%, slightly lower than some other methods such as multi-LSTM and ANN utilizing specific techniques. Each method has its strengths and areas for improvement, highlighting the diversity of approaches in islanding detection using machine learning. Further research could focus on refining CNN architecture, exploring novel feature extraction methods, and integrating additional data sources to enhance detection accuracy and robustness.

The analysis of islanding detection techniques encompasses both Time Series classification methods and image analysis techniques, showcasing promising outcomes. Utilizing Time Series classification techniques, specifically XGBoost and LSTM, for voltage sags/swells analysis resulted in remarkable accuracy, reaching 99.6%. These models exhibited exceptional precision, recall, and F1-score, highlighting their robustness in predicting voltage events with precision. Conversely, the utilization of image analysis techniques, particularly Convolutional Neural Networks (CNNs), for islanding detection presented consistent and impressive results. CNNs demonstrated high accuracy across various protection measures, with an overall average accuracy of 92%. While both approaches offer valuable insights into power system monitoring and management, each method showcases its strengths and areas for further optimization.

Chapter 7

Conclusions

Chapter 7 Conclusions

This chapter highlights the main research findings, recommendations for future work, and recommendations and guidelines for the work that has been carried out in this research.

7.1 Main Research Findings

The main research findings are provided through the achievement of the research objectives as follows:

The comprehensive study conducted to assess the effectiveness of Convolutional Neural Networks (CNNs) in detecting islanding conditions in power systems has yielded insightful and promising results. This conclusion synthesizes the findings from the analysis of ten different electrical protections, each crucial for the stability and safety of power grids. These protections include Frequency in Hz, Rate of Change of Frequency, Over Voltage, Rate of Change of Voltage, Rate of Change of Power, Rate of Change of Reactive Power, Voltage Total Harmonic Distortion, Current Total Harmonic Distortion, Voltage Negative Sequence Distortion, and Current Negative Sequence Distortion.

A pivotal aspect of this study is the successful application of CNNs, a domain traditionally reserved for image processing and analysis, to the realm of power system monitoring and control. By treating electrical signal patterns as images, this approach demonstrates an innovative way to utilize advanced machine learning techniques in electrical engineering. The model's ability to discern subtle patterns in these 'images' allowed for a nuanced understanding of islanding conditions, showcasing the versatility and adaptability of CNNs.

The precision and recall metrics obtained across different protections reveal the depth and efficacy of CNNs in this context. Notably, protections like Over Voltage and Current Total Harmonic Distortion achieved perfect scores in precision, recall, and accuracy, underscoring the model's exceptional capability in identifying both islanding and non-islanding conditions without errors. This level of accuracy is particularly crucial in power systems, where false positives or negatives can lead to inefficient operation, equipment damage, or even safety hazards.

However, the study also uncovered areas where the model's performance could be enhanced. For instance, in the Frequency in Hz and Voltage Negative Sequence Distortion protections, the model showed a tendency towards false negatives and positives, respectively. These findings highlight the need for further fine-tuning of the CNN models, potentially through more extensive training datasets, improved feature extraction, or advanced neural network architectures.

The study used 1000 trends across various parameter protections to train, validate, and test the model. Overall accuracy rates were mostly above 94%, highlighting the potential of these models as reliable tools for islanding detection across various protections. Additionally, ten CNN algorithms have been built, with one CNN algorithm dedicated to each protection parameter. The overall average accuracy achieved was 92%, based on 100 trends of each protection parameter. The accuracy of time series analysis for voltage sags and swells was 99.6% using XGBoost and LSTM, demonstrating the high effectiveness of these methods in precise islanding detection.

The overall accuracy rates, ranging mostly above 94%, are a testament to the CNN's potential as a reliable tool for islanding detection. These high accuracy

levels are indicative of the model's robustness and its ability to handle the variability and complexity inherent in power system signals. Moreover, the consistency of these results across a diverse set of protections underscores the adaptability of CNNs to different aspects of power system monitoring.

In conclusion, this study marks a significant step forward in the application of machine learning in the realm of power systems. The impressive performance of CNNs in detecting islanding conditions across various protections offers a glimpse into a future where artificial intelligence plays a central role in grid management and stability. It opens up new avenues for research and development, particularly in optimizing these models for real-time application and integrating them with existing grid infrastructure. As the energy sector continues to evolve with increasing integration of renewable sources and the push towards smarter grids, the role of advanced technologies like CNNs becomes ever more critical. This research not only demonstrates the feasibility of such an integration but also paves the way for more innovative, data-driven approaches to ensure the reliability, efficiency, and safety of power systems worldwide.

In addition to its technical prowess, the deployment of CNN-based islanding detection systems offers significant benefits from an engineering management perspective. The high accuracy rates achieved by the CNN model, mostly above 94%, indicate a high level of reliability in identifying islanding events, thereby reducing the risk of costly power outages and equipment damage. This reliability translates into tangible cost savings for utility companies by minimizing downtime and maintenance expenses associated with grid disturbances. Furthermore, the adaptability of CNNs to different aspects of power system monitoring suggests potential for streamlined operations and

resource optimization within utility organizations. By integrating CNN-based detection systems into existing grid infrastructure, engineering managers can enhance the overall efficiency and resilience of their power networks while simultaneously reducing operational costs.

Moreover, the implementation of CNN-based islanding detection systems aligns with broader trends in engineering management towards leveraging advanced technologies for improved decision-making and resource allocation. By investing in innovative solutions such as CNNs, utility companies demonstrate a commitment to staying at the forefront of technological advancements in the power sector. This proactive approach not only enhances grid reliability and resilience but also enhances the company's reputation as an industry leader in innovation and sustainability. Additionally, the integration of CNN-based detection systems into existing engineering management frameworks enables data-driven decision-making and proactive maintenance strategies, further optimizing asset performance and minimizing downtime. As such, the adoption of CNNs for islanding detection represents a strategic investment for utility companies seeking to enhance operational efficiency, reduce costs, and maintain a competitive edge in the rapidly evolving energy landscape.

7.2 Recommendations for Future Work

From this thesis, the following recommendations for future work are suggested:

- Investigate the feasibility of real-time implementation of islanding detection algorithms in power systems. Additionally, focus on optimizing

these algorithms for faster and more efficient performance, enabling timely responses to potential islanding events.

- Explore the integration of data from multiple sensors or sources (such as IoT devices, smart meters, or distributed sensors) to enhance the accuracy and reliability of islanding detection. Investigate how combining various data sources could provide a more comprehensive understanding of system behavior and improve detection capabilities.
- Develop detection methods that are robust and adaptable to dynamic changes in power system configurations, load variations, renewable energy integration, and other evolving system parameters. This involves studying methods that can continuously adapt to changing conditions without compromising accuracy.
- Consider incorporating cybersecurity measures and resilience into islanding detection systems to mitigate potential cyber threats or attacks that could compromise the reliability and security of power systems.
- Establish standardized evaluation metrics, benchmarks, and protocols for assessing the performance of islanding detection methods. This will facilitate fair comparisons between different approaches and aid in the advancement of the field.
- Conduct a comprehensive cost-benefit analysis of implementing various islanding detection techniques. Evaluate the economic implications, including the cost of implementation versus the potential benefits in terms of system stability, reliability, and outage prevention.
- Explore the integration of explainable AI techniques to enhance the interpretability and transparency of islanding detection models. This is

crucial in critical infrastructure like power systems where understanding the decision-making process is essential for trust and reliability.

By addressing these additional facets in future research endeavors, the field of islanding detection in power systems can advance further, leading to more robust, efficient, and reliable methods for identifying and preventing islanding events.

7.3 Recommendations and Guidelines for this Research

Further recommendations and guidelines for the work that has been achieved in this research are provided accordingly:

- Refinement of image classification-based islanding detection can be achieved by extending monitoring to encompass additional parameters. The effectiveness of the islanding detection method stands to benefit from a more comprehensive approach involving the monitoring of a wider array of parameters.
- There is a need for more comprehensive studies focusing on early islanding detection through the continuous monitoring of both fault and normal operating conditions. The implementation of statistical methods holds promise in developing more robust indices, thereby enabling more effective early islanding detection.
- Improving machine learning or deep learning models requires access to larger datasets that encompass a greater number of parameters. Enhancing the learning process of features and boosting classification accuracies can be achieved through the creation of expansive datasets. Additionally, the

absence of a standardized dataset or system for testing islanding detection methods presents an opportunity to establish a standardized dataset akin to ImageNet in the realm of image classification research.

- Augmenting classification accuracy can be accomplished through the utilization of ensemble machine learning or deep learning models.
- Beyond islanding detection, the image classification-based approach holds potential for broader applications, such as power quality event classification and power system fault classification. Exploring these alternative applications could lead to further advancements in the field.

In summary, future research endeavors should encompass expanding parameter monitoring, refining statistical methodologies, acquiring larger datasets, establishing standardized testing systems, utilizing ensemble models, and exploring diverse applications beyond islanding detection.

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الملخص

يمثل التوليد الموزع (Distributed Generation) والذي يكون مربوط بشبكة نقل واحدة استراتيجية ضرورية لتلبية الطلب المتزايد وتحسين موثوقية امداد الطاقة للمشاركين خصوصا مع زيادة مصادر الطاقة المتجددة بالشبكة. ان ربط كل هذه المولدات في شبكة واحدة قد يؤدي الي احتمال خروج جميع المولدات بشكل كامل وحدث انطفاء كلي بالشبكة في حالات حدوث اضطرابات او أخطاء بالشبكة. لذلك كان ضرورية عمل هذا المولدات بشكل منفصل في حالات اضطراب الشبكة لتفادي خروج الوحدات وحدث انطفاء كامل بالشبكة فكان من الضروري إيجاد نظام امن وسريع للكشف عن حالات الاضطراب بالشبكة وتحويل عمل هذا المولدات في وضع جزر كهربائية مستقلة تعمل بشكل منفصل عن الشبكة . بالإضافة الى ذلك ومن منظور الإدارة الهندسية ، يتطلب تنفيذ أنظمة موثوقة للكشف عن الجزر دراسة متأنية لاختيار التكنولوجيا وتكامل النظام التشغيل و الصيانة لوضع معايير واضحة وضمان الامتثال وتحسين أداء النظام. ومن خلال معالجة هذه الاعتبارات الإدارية ، يمكن تحقيق الدمج السلس للإدارة العامة في شبكة المرافق مع إعطاء الأولوية للسلامة والموثوقية والكفاءة التشغيلية. هناك العديد من الاستراتيجيات تم كشفها لتعرف على حالات الجزر الكهربائية لتعزيز سرعة الكشف ودقته. ومع ذلك ، تتطلب هذه الأساليب ضخ قدرات الذكاء الاصطناعي لضمان الدقة وتفادي الضوضاء كهربائية. يقترح البحث المقدم هنا استخدام أساليب تصنيف الصور للكشف عن الجزر حيث يتم تحويل البيانات الكهربائية من نقطة الاقتران المشترك بين المولدات والشبكة إلى صور. ومن ثم التعرف على أنواع الأعطال واتخاذ القرار المناسب بتحويل النظام الى جزر كهربائية مفصولة او لا. تم تصميم نموذج نظام كهربائي ديناميكي محاكي للحصول على مجموعة بيانات شاملة تمثل مختلف سيناريوهات الجزر وغير الجزر ويمكن من خلال تدريب واختبار والتحقق من صحة التعلم الآلي وخوارزميات التعلم العميق. تستخدم هذه الدراسة الشبكة العصبية التلافيفية (Convolutional Neural Network (CNN)) لتقنيات الكشف عن الجزر. ميزة هذا الابتكار هو التعرف والكشف المبكر عن الجزر عن طريق مراقبة الأخطاء بالشبكة ومقارنتها بالعمليات العادية ، تم عمل خوارزميات خاصة لتعرف والتحقق من صحة النموذج المقترح وفحصه باستخدام مجموعة بيانات خاصة مصممة للجزيرة والتي تحتوي على حالات تكون فيها الطاقة غير مستقرة والبيانات فوضوية. لقد أظهرت هذه الطريقة مدى فعالية تصنيف الصور في تحديد سيناريوهات الجزر وإمكانية استخدامها لها لها من فعالية وسرعة تساعد على موثوقية تدفق الطاقة بشكل امن ومستمر.

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استخدام الذكاء الاصطناعي للكشف عن حالات جزر المولدات في الشبكة الكهربائية في تذبذب الجهد

أطروحة مقدمة كجزء من متطلبات الحصول على درجة
دكتوراه الفلسفة في الإدارة الهندسة

إعداد

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