FAULT DETECTION AND IDENTIFICATION FOR DC MICROGRID WITH WAVELET-BASED ARTIFICIAL NEURAL NETWORKS

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Submitted by

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DECLARATION

I hereby certify that the work which is presented in the dissertation entitled, **"Fault Detection and Identification for DC Microgrid with Wavelet-based Artificial Neural Networks"**, in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Power Systems, submitted to Electrical & Instrumentation Engineering Department of Thapar Institute of Engineering & Technology (Deemed to be University) is as authentic record of my work carried under the supervision of **Dr. Prasenjit Basak**. It refers to others researchers' work which is duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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NOMENCLATURE

$A_1(n)$	Approximate wavelet coefficient at the first level of decomposition
$D_1(n)$	Detailed wavelet coefficient at the first level of decomposition
$\Psi_{(x,y)}(t)$	Family wavelet
$g(n)$	High pass filter coefficient
$h(n)$	Low pass filter coefficient
$\psi(t)$	Mother wavelet
x	Scaling parameter
y	Translation parameter

ABBREVIATIONS

ANN	Artificial Neural Network
BESS	Battery Energy Storage System
CWT	Continuous Wavelet Transform
DCMG	DC Microgrid
DERs	Distributed Energy Resources
DT	Decision Tree
DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transform
KNN	K Nearest Neighbor
MLP NN	Multilayer Perceptron Neural Network
MPPT	Maximum Power Point Tracking
PG	Pole–to-Ground
PP	Pole-to-Pole
SOC	State of Charge
STFT	Short Time Fourier Transform
VSC	Voltage Source Converter
WT	Wavelet Transform

ABSTRACT

The widespread implementation of DC microgrids (DCMGs) is a significant step toward future power systems' ability to match load requirements with distributed generation precisely. DC microgrid has become a viable alternative for increasing DC applications and load needs compared to AC microgrid. However, the DC microgrid system's thriving potential is hampered by the significant challenges associated with its protection. The challenges arise due to the time constraints imposed by rapidly increasing fault currents in DC systems, an absence of frequency and phasor information, and the absence of a natural zero crossing of DC fault current. Furthermore, altering DC microgrid topologies impacts the existing protection mechanisms significantly. As a result, for the DC microgrid to operate adequately, an intelligent protection strategy is required.

This work presents intelligent fault detection and identification approach for DC microgrids based on wavelet transform (WT) and artificial neural networks (ANNs). In this work, firstly, the wavelet transform is applied for pre-processing the current signals to determine the detailed wavelet coefficients. Then, the maximum value among the detailed coefficients, which provides critical information during fault events, is used to construct the input feature vector. After extracting the fault characteristics, the data set, consisting of input feature vector along with output tags, is utilized for training an Artificial Neural Network (ANN) model to identify and categorize faults in DCMGs. For data collection, the study simulates diverse fault types, fault locations, fault resistance, and fault incident time and no-fault (load variation) scenarios under both grid-parallel and off-grid operating modes. MATLAB/Simulink software has been used to run the simulations on a PV-based DC microgrid. The proposed scheme's test analysis using ANN verifies the scheme's reliability and efficiency in providing potential DC microgrid protection.

Keywords: DC Microgrid, Distributed generation, Wavelet transform, Artificial neural network, Fault detection and classification.

CHAPTER 1
INTRODUCTION

1.1. OVERVIEW

In this era of rising energy demands and increasing public awareness of the environmental impacts of traditional electric power generation, the microgrid concept advances for optimizing the contributions of distributed energy resources (DERs) integrations into the distribution sector. A microgrid is a planned, controlled, and protected power island that may operate in grid-parallel or off-grid mode and has a well-defined electrical boundary [1]. The coordinated control of microgrid resources improves energy efficiency, lowers energy consumption, and minimizes energy production's environmental effect.

The conventional approach to microgrid design and deployment is typically achieved with the aid of the AC system [2]-[3]. However, the DC microgrid has gained substantial attention in recent years compared to conventional AC microgrid systems due to the following reasons [4]-[5].

- Since most distributed generators (PV, fuel cell, etc.) output DC, a DC microgrid makes it easier to incorporate them into the existing distribution sector.
- A DC microgrid is so configured that it eliminates the need for synchronization and reactive power control.
- DC microgrid offers a distinct advantage while delivering power to isolated, rural, hilly places where the present infrastructure is challenging or economically unsustainable.
- Due to reduced losses and fewer power conversion stages, DC microgrids are more efficient than their AC counterparts.
- DC microgrids provide increased power transfer capabilities, enhanced reliability, and lower operation and maintenance expenses.

However, technological challenges associated with DC microgrid design, operation, control, and protection prevent its widespread implementation. The design of an adequate protection mechanism is one of the significant obstacles to the actual deployment of a DC microgrid. The system must meet the main protective requirements of sensitivity, stability, reliability, and selectivity under both grid-parallel and grid-isolated operating modes.

Furthermore, the protective mechanism should be capable of adjusting to the varying operational conditions.

1.2. DC MICROGRID PROTECTION

Despite the numerous advantages of DC microgrids, the trend toward their adoption faces a significant challenge: DC microgrid protection. An efficient protection system is necessary to ensure adequate security, selectivity, sensitivity, and redundancy. Inadequate DC microgrid protection can raise the risk factor, particularly for sensitive DC loads. Following are a few of the most critical issues to consider when it comes to the protection of DCMG systems [6]-[7]:

i. *Non-availability of natural zero crossing:* In case of DC faults, for arc extinguishment, the performance of circuit breakers is inefficient owing to the absence of a natural zero crossing current, thus necessitating the inclusion of an additional device to make the DC zero. Furthermore, in DC systems, the absence of zero-crossing current poses a severe risk to personal safety in addition to causing contact erosion in circuit breakers, thereby shortening their lifespan [8].

ii. *High sensitivity of inverters to fault current:* Microgrid inverters possess limited fault current capacity. Due to the low fault current level in this scenario, this problem is more concerning in grid-parallel mode than in off-grid mode. Current-based relays' coordination and sensitivity are impacted due to this low fault current level, potentially causing relay delays. Inverters between the grid and the microgrid can even have constrained performance owing to their high sensitivity towards higher fault currents. This problem must be addressed to improve the fault tolerance and flexibility of the inverters in binding the fault.

iii. *Less inertia and low stability:* Due to AC side disturbances, which generate temporary faults on the DC side, interconnected DC microgrids suffer from severe power instability and oscillation difficulties. In addition, instability and power oscillation make it challenging to distinguish between a power swing and a fault. Moreover, the DC microgrid's low stability and inertia also hamper the fault restoration mechanism.

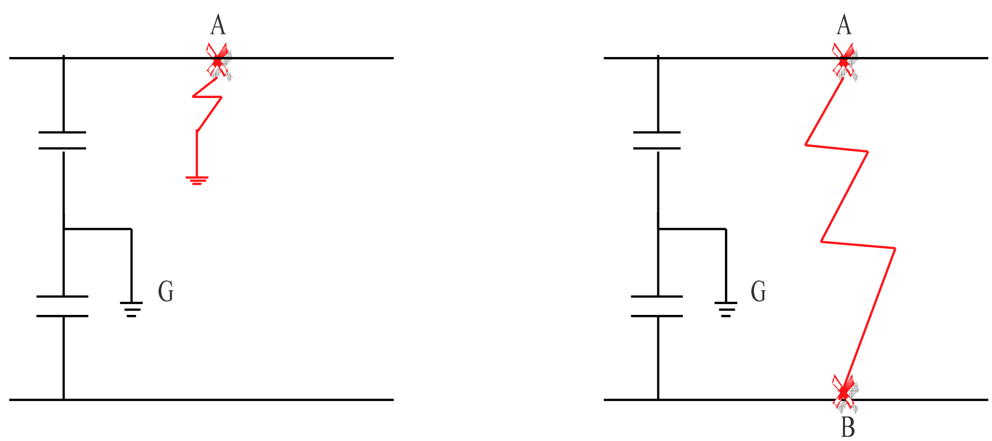
iv. *Grounding:* In a DC microgrid, proper grounding is critical with the primary objectives of enabling fault detection, fulfilling protection standards, and ensuring the security of both equipment and personnel. The fault current magnitude is greatly influenced by the fault type, grounding resistance, and grounding system components, which can provide a significant fault detection challenge in case of over-current relays.

1.3. FAULTS IN DC MICROGRID

As microgrid components are vulnerable to high fault currents, monitoring and evaluating short-circuit fault currents is critical for developing an effective fault protection strategy. Short circuit faults can develop in DCMGs in two ways [9]-[10]:

i. *Pole-to-ground (PG) fault:* A pole-to-ground fault occurs when a short-circuit exists between one of the system's poles and the ground as shown in Fig.1.1 (a). PG fault is either a high or low impedance fault [11]. PG faults are the most frequent in the system, although they are less harmful, fortunately.

ii. *Pole-to-pole (PP) fault:* A pole-to-pole fault arises whenever the positive and negative lines of a system come into direct contact as depicted in Fig.1.1(b). PP faults have low fault impedance characteristics and thus can cause severe system damage.



(a) Pole to ground (PG) fault (b) Pole to pole (PP) fault

Fig. 1.1: Faults in DC microgrids

Therefore, an attempt has been made to develop intelligent fault detection and identification strategy for DC microgrids (DCMGs) utilizing wavelet transform (WT) and artificial neural networks (ANNs). This work aims to obtain fault signal characteristics by employing WT and then using those features for training an artificial neural network (ANN) to identify and categorize faults in DCMGs. Simulations and analysis are carried out using

MATLAB/Simulink. Various types of faults, like pole-to-ground and pole-to-pole faults, are studied and tested to ensure the efficiency of the suggested protection strategy.

1.4. DISSERTATION OUTLINE

Chapter 1 discusses a brief review of the microgrid, the benefits of the DCMG over the AC microgrid, and various challenges that are encountered while implementing any potential DCMG protection scheme. Also, it presents a brief idea about different types of short-circuit faults that occur in DCMG.

Chapter 2 discusses the literature review of various protection techniques employed for DC microgrid protection. It briefly reviews the fuzzy logic-based, ANN-based, and wavelet transform-based protection techniques for DCMG protection.

Chapter 3 presents the topology of the DCMG model used in this work. It also discusses the suggested fault detection and classification strategy and its functioning flowchart. The chapter also discusses the application of wavelet transform for fault feature extraction and ANN for fault detection and identification.

Chapter 4 presents the results obtained by simulation of DCMG under grid-parallel and off-grid operating modes. It also discusses test result analysis for fault detection and identification using ANN. In addition, the performance evaluation and the accuracy computation of the suggested protection scheme using the confusion matrix and the F1-score, which depicts the scheme's reliability and efficiency in providing potential DC microgrid protection have been discussed.

Chapter 5 summarizes the work carried out in this dissertation and presents the need for accurate fault detection and classification techniques for DC microgrids. It also covers the future prospect of the work followed by a list of publications, references, appendix, and plagiarism report.

CHAPTER 2
LITERATURE REVIEW

This chapter presents a brief description of different DC microgrid protection techniques discussed in the literature. Fuzzy logic, ANN, and wavelet transform-based protection schemes for DCMGs have also been discussed. The chapter in the later section discusses the research gaps and the objectives of the study.

2.1. REVIEWS ON DC MICROGRID PROTECTION TECHNIQUES

Microgrids are gaining popularity as a result of their environmental benefits and cost-effectiveness, in addition to reduced power losses and minimal infrastructure. They do, however, face several operating difficulties, including power system instability, power quality, reliability, and protection concerns [12]. The protection of microgrids is a critical challenge for their reliable functioning. [13]-[14] provides an overview of AC and DC microgrids through a comprehensive review. The most current advancements in AC and DC microgrid protection strategies are thoroughly examined and categorized in [13]. A comparison of several protection approaches is also done in order to help researchers identify the most reliable protection systems for microgrids. The key issues with AC and DC microgrids are classified in [14], and then existing and promising approaches for each challenge are investigated.

The substantial advantages of DC microgrids have prompted extensive attempts to make them a viable alternative to traditional AC power networks. Even though their deployment is increasing, there are still several barriers to designing, controlling, and operating DCMGs in both grid-parallel and grid-isolated operating modes. As a result, extensive research is being conducted to address these challenges. The DC microgrid design, standards, protection challenges, and conventional as well as new protective methods have all been thoroughly reviewed methodically and chronologically in [15]. Furthermore, taking into consideration the various operating modes and configurations of the microgrid, the futuristic possibility of inventing a new comprehensive strategy based on the latest innovation and methodology is represented by a more secure, efficient, and effective protective mechanism to prevent faults in the power network. Current state-of-the-art issues in DCMG fault management are discussed in [16]. It covers research in areas like fault identification, detection, localization, isolation, and reconfiguration in DC microgrids. To evaluate the fault management of DC microgrids, a detailed review is conducted in each area. Finally, emerging trends and obstacles in the field of DC microgrid fault management are considered.

2.1.1. Fuzzy Logic based protection techniques in DCMGs

For LVDC microgrids, a new fault recognition approach based on fuzzy logic is suggested in [17]. Based on the defined rules and conditions, a fuzzy logic system provides the best and optimal choice for each mode of the DC microgrid. The fuzzy system seeks to enable rapid fault identification in microgrids using instantaneous current monitoring, independent of the type of fault and current magnitude, along with the power supply's feeding capabilities, by isolating the faulty part while the remaining healthy segment operates properly. [18] presents a protection strategy for a low voltage ring DCMG employing a differential protection mechanism by fuzzy systems. The protection mechanism recognizes all types of DC faults for high and low impedance faults and safeguards the entire network from being shut down. Following the recognition and isolation of the fault, the location of the fault has been determined using voltage transients and fuzzy logic.

2.1.2. Artificial Neural Network (ANN) based protection techniques in DCMGs

ANN has gained considerable attention in the power system network for fault identification and classification due to its enhanced flexibility and dynamic nature of work. The fault signal is fed into the ANN, which estimates the fault status as an output. [19]-[20] demonstrates the need for an artificial neural network (ANN) for detecting as well as locating faults in a low-voltage DCMG. It allows faults on the DC bus to be rapidly diagnosed and isolated keeping the healthy system intact, thereby resulting in a more resilient DCMG. Using Multi-Layer Perceptron Neural Network (MLP NN), [21] proposes an accurate protection approach for low-voltage DC ring-bus microgrid. The suggested technique uses instantaneous current monitoring of each microgrid segment to estimate accurate fault location in microgrids, irrespective of the fault current type and magnitude. The study reveals that the fault location estimation error is low and within acceptable limits. The effectiveness and accuracy of MLP NN are validated by the results.

A protection method for LVDC microgrids with multiple DGs and storage is presented in [22]. For fault detection, the differential current and its first derivative are analyzed using the decision tree (DT) method, and fault classification is done using the K-nearest neighbor

(KNN) approach. With variations in microgrid configurations and modes of operation, the resilience of the suggested protective strategy is evaluated with respect to various types of faults. Noise impacts, the intermittent nature of DGs, and evaluation under external fault conditions and crucial non-fault instances have all been investigated. MATLAB/Simulink is used to evaluate the suggested strategy. The results of the tests show that the suggested technique can identify and categorize faults with high accuracy and speed. [23] focuses on the development of a low-cost protective mechanism enabling rapid diagnosis, selective disconnection of high-impedance faults, and system reconfiguration in DCMGs without solid-state breakers. For each source converter and contactor, high impedance faults are detected using a multi-resolution evaluation of locally recorded current signals using a discrete wavelet transform and a K-nearest neighbor-based classifier.

2.1.3. Wavelet Transform (WT) based protection techniques in DCMGs

To identify faults, current DC fault detection techniques use hard thresholds [24]. These techniques' accuracy is easily influenced due to network operations or interruptions. Pattern recognition approaches eliminate this shortcoming by using soft criteria for fault recognition and identification. It enables the quick and accurate identification of network faults by comparing fault features. To derive fault characteristics and identify faults, several signal analysis and pattern recognition approaches have been utilized. The most widely employed signal processing techniques involve time series analysis, fast Fourier transform (FFT), short-time Fourier transform (STFT), and wavelet transform (WT). Time series analysis has the inherent limitation of being unable to capture any signal frequency information. Although FT is capable of retrieving all frequency information from the signal, the time variable is omitted. While STFT is capable of monitoring time as well as frequency, it is limited by time frame constraints. A limited time window provides better temporal resolution but poor frequency resolution, whereas a wide time window provides high time resolution but poor frequency resolution. WT modifies the frequency and time scale resolution by using a variable time window size. As a result, WT is better adapted for extracting characteristics of abrupt changes induced due to network faults [25].

[26] suggests a pattern recognition-based fault detection technique. It extracts the essential characteristics using a multi-resolution signal decomposition technique, after which a fuzzy logic system assesses whether or not a fault is developed. The proposed case studies (simulated and experimental) show that the suggested technique is efficient and reliable in

identifying faults. [27] suggests wavelet energy fuzzy neural network-based approach for executing fault mitigation for the grid-connected microgrids. Using this technique, the dominating features of fault signals are appropriately retrieved by fuzzy analysis. The experimental outcomes show that the suggested technique can accurately identify faults and then activate the protective relay in real-time to disconnect the microgrid from the utility grid. Using wavelet packets, the work presented in [28] provides a simple defect detection approach based on available array voltage and current data. To evaluate its performance, the suggested scheme is modeled using MATLAB/Simulink and empirically validated on a 1.6-kW 4x4 PV array.

[29]-[30] provides smart fault detection and identification technique for DC microgrids employing WT and ANN. It focuses on using WT to extract fault signal features and then train an ANN using these features that can identify and categorize faults in DCMGs. For simulations and evaluations, PSCAD/EMTDC and MATLAB are employed. Different fault types are evaluated and tested, including PP faults, PG faults, and AC grid faults, to ensure that the suggested approach is effective. For DC ring bus microgrids, two-level hierarchical fault diagnosis and location systems are presented in [31]. For identifying PP and PG faults despite measurement noises and disruptions in load, a decentralized fault diagnosis approach using back propagation (BP), artificial neural network (ANN), and discrete wavelet transform (DWT) is presented at the primary level. At the secondary level, an approach for localization of distributed line faults is proposed by combining the detection outcomes of local and neighboring DG units via low bandwidth communication, and the efficiency of line fault detection is significantly enhanced without using a central controller or extra sensors. In various simulation cases, different fault configurations like types of fault, load variations, fault locations, and fault impedance are investigated.

[32] provides a wavelet-based fault identification approach for a microgrid that is independent of fault current level. Using the wavelet transform, the fault current signal is decomposed to retrieve significant fault current characteristics. These characteristics involve the difference in standard deviation, entropy, and energy of pre-fault and post-fault current cycles. In a modified IEEE 13-Node test feeder with renewable energy-based DERs operating in off-grid and grid-parallel modes, the suggested technique is tested for faults. The test results show that the suggested technique can discriminate between faults and system disruptions, paving the way for the deployment of an effective microgrid protection scheme.

However, there remains a research gap for accurate fault detection and identification techniques for DC microgrids. The majority of available fault detection and classification approaches employing signal processing and data-driven methodologies focus on AC distribution networks. Most DCMG protection approaches currently rely on communication among devices which poses a number of implementation challenges. Furthermore, DCMG protection based on current signal processing and data-driven strategies need to be improved in order to solve challenges like noise sensitivity and complicated algorithms that contribute to prolonged fault detection times.

2.2. GAPS IN RESEARCH

Following are the gaps found in the research based on the literature survey:

i. Fault detection and identification by extracting fault features using wavelet transform is less explored for DCMGs.
ii. Fault feature extraction by obtaining the maximum value among the detailed wavelet coefficients for DCMG is not studied.
iii. The effect of SOC variation has also been considered while simulating the test cases by operating the DCMG in the islanded mode, which is different from previous literature.
iv. Application of a certain fault detection and identification scheme while operating the DCMG in both off-grid and grid-parallel operating mode with a high level of accuracy and precision is rare.

2.3. OBJECTIVES OF STUDY

Protection issues in microgrids have a significant impact on power system reliability owing to high distributed generator penetration levels. Consequently, the protection of microgrids against faults is critical and must be addressed in order to improve the power system's robustness. This work aims to present a smart fault detection and identification strategy for DC microgrids employing wavelet transform (WT) and artificial neural networks (ANNs). Thus, based on the aim of the work and the found gaps in research, the following objectives have been set for this dissertation work:

i. Modeling and simulation of a test model of a DC microgrid consisting of a PV system with battery using MATLAB/Simulink.

ii. Application of wavelet transforms for fault detection and identification by extracting the characteristics from the faulty current signal.
iii. Collection of data by extracting the maximum value among the detailed wavelet coefficient and utilizing this data-set to identify, and categorize faults using the ANN classifier.
iv. Validation of proposed wavelet-based ANN fault detection strategy for the test DCMG model.
v. Exploring the reliability and accuracy of the proposed protection strategy for both grid-parallel and off-grid operating modes.

CHAPTER 3
METHODOLOGY

This chapter includes a PV-based DCMG developed using MATLAB/Simulink. Also, the proposed fault detection and identification algorithm have been presented. A brief idea about wavelet transform (WT), and feature extraction using WT has also been discussed. In addition to this, Artificial Neural Network (ANN) architecture, its training, and testing have been discussed.

3.1. DC MICROGRID ARCHIRECTURE

Fig.3.1 depicts a schematic of a photovoltaic-based DC microgrid with an integrated battery energy storage system (BESS) built in MATLAB/Simulink. The PV array is linked to the DC bus through a boost converter and BESS using a bidirectional buck-boost DC-DC converter, that is linked using a voltage source converter (VSC) to the utility power system. The PV is set at maximum power point tracking (MPPT) mode, with temperature and irradiance determining power output.

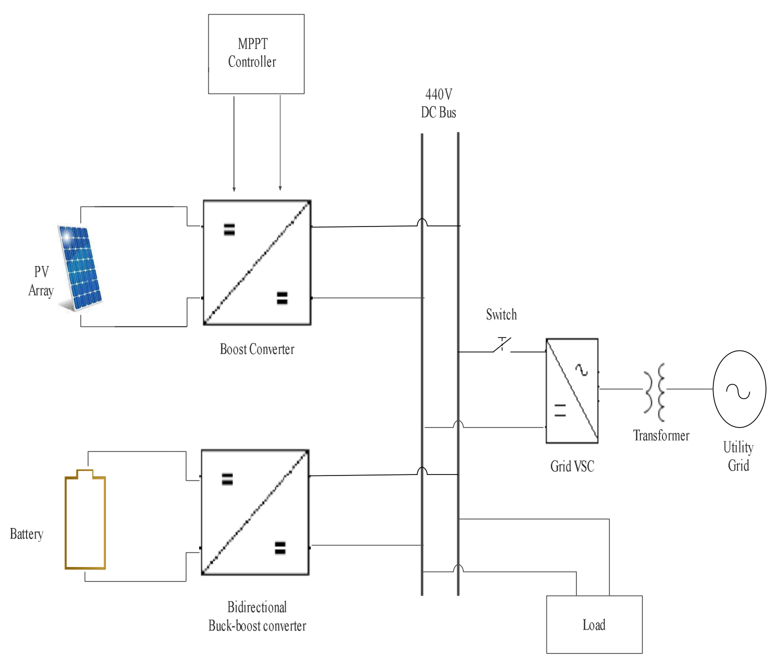


Fig. 3.1: DC Microgrid schematic diagram

The DCMG incorporates a radial topology with a 440 V DC nominal bus voltage. The DC microgrid functions in either grid-parallel or off-grid operating mode. Table I lists all the microgrid parameters.

Table I: DCMG model parameters

Parameters	**Values**
Grid	1MW, 11kV,50Hz
PV rating	100kW
Battery Storage	160V, 600Ah
Line L1	R= 0.1284 Ω
Line L2	R=0.0642 Ω, L=26.4μH
Line L3	R=0.322 Ω, L=1.21mH
Dc bus voltage	440V
Load	75kW

3.2. PROPOSED FAULT DETECTION AND IDENTIFICATION SCHEME

The suggested fault detection and identification approach uses wavelet transform (WT) for extracting fault features from the monitored current signal, followed by a pattern recognition method enabling feature comparison and fault diagnosis. Fig.3.2 depicts the suggested fault detection and identification algorithm's flowchart.

For data acquisition, monitored signals are sampled, and the discrete wavelet transform (DWT) is employed for decomposing the signal into time-localized frequency bands. The DWT outputs a set of detail coefficients that requires a lot of memory and processing time if used directly for classification. As a result, appropriate features that reflect the input signal's characteristics are selected.

In the proposed technique, a statistical feature - maximum value among the detailed wavelet coefficients, which provides critical information during fault events, is used to construct the input feature vector. After extracting the fault characteristics, the input feature vector is utilized to identify and categorize faults with a pre-trained feed-forward artificial neural network (ANN).

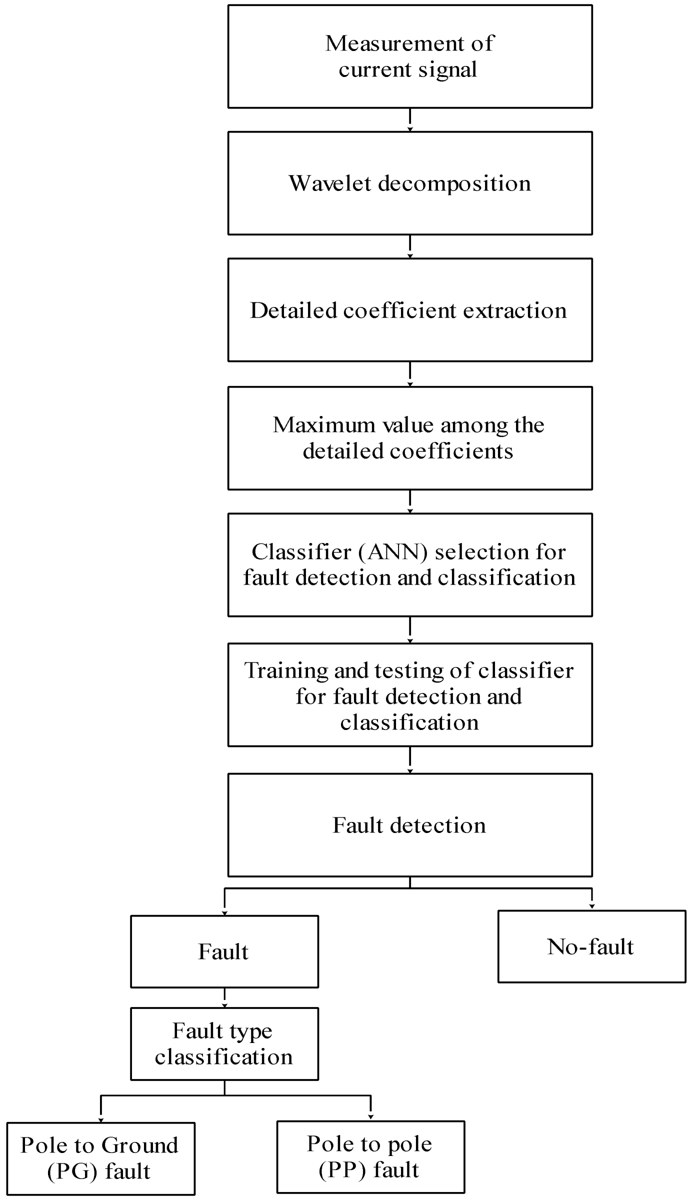


Fig. 3.2: Flowchart of the proposed fault detection and identification scheme

3.3. WAVELET TRANSFORM AND FEATURE EXTRACTION

The Wavelet Transform (WT) is a signal processing method that is extensively utilized for applications in power system research. A wavelet representation of a signal presents a precise measurement of the frequency variations of the signal over time. Due to the WT's potential to localize a signal in temporal as well as frequency domains, it can detect and locate sudden changes in signals [33]. In the suggested fault detection and identification approach, WT acts as a key component in extracting fault output.

3.3.1. Wavelet theory

A wavelet is defined as a wave that occurs for a short period and has a zero mean value. Any time signal may be constructed using time-shifted and scaled variants of a unique admissible mother wavelet [34]. The wavelet transform decomposes the sampled signal into detail and approximation coefficients. It functions as a combination of high-pass and low-pass filters. The high pass filter outputs the detail coefficients, which capture the signal's higher frequency component. The approximation coefficients, or the lower frequency component of the signal, are the output of the low-pass filter. They can be split further into approximation coefficients and detail coefficients for approximation coefficients [35]-[36].

There are a variety of wavelet families that may be utilized as mother wavelets in WT analysis, including - Coiflets family (coifN), Daubechies family (dbN), and Symlets family (symN), where N represents the wavelet function order. Features like orthogonality, symmetry, vanishing moments, etc. are generally used to distinguish among mother wavelets. When choosing a mother wavelet, these characteristics must be taken into account. The optimal choice would be to use the mother wavelet, which has properties that are quite similar to the signal under evaluation [37]. While evaluating power network signals, which often include a lot of transient components, Daubechies (db) wavelets act as a good choice for the mother wavelet. They exhibit a high temporal resolution, thereby allowing reliable detection of fast transients caused by faults. Moreover, they outperform other wavelets in signal recognition and noise reduction. As a result, the db wavelet family has been selected for analysis in this work.

Among the dbN wavelet series, db1-db10 is the most widely utilized. In this work, the efficiency of the classifiers originating from each wavelet series is used to select dbN series wavelets. Using a trial-and-error technique, the initial investigations using wavelets db1-db10 revealed that the db4 wavelet produces the greatest classification accuracies for this application. As a result, the db4 mother wavelet has been selected since it will deliver the optimum fault detection and classification outcomes.

Another factor that influences signal feature extraction is the decomposition level. The level of decomposition is chosen in such a way as to obtain all of the signal's high-frequency information required for feature comparison. A higher decomposition level, on the other hand, results in a greater computational burden [38]. As a result, the appropriate decomposition level must be carefully selected. Consequently, the current signal is split into detail and approximate coefficients at the first level for feature extraction in this study.

Mathematically, the WT of a given signal in relation to a mother wavelet is defined in the continuous domain. The continuous wavelet transform (CWT) defines the relation between the signal *f(t)*, and the family wavelet $\psi^{*}_{(x,y)}(t)$ corresponding to each x and y, and is expressed as [39]:

$$W_{(x,y)}(t) = \int_{\infty}^{-\infty} f(t)\psi^{*}_{(x,y)}(t)dt \qquad 3.1$$

where, x and y denote scaling and translation parameters, respectively with $x, y \varepsilon R; x \neq 0$. The mother wavelet $\psi(t)$ is scaled and translated to generate a set of elemental functions called a family wavelet $\psi^{*}_{(x,y)}(t)$.

$$\psi_{(x,y)}(t) = \frac{\psi}{\sqrt{x}}\left(\frac{t-y}{x}\right) \qquad 3.2$$

CWT generates a large number of coefficients, resulting in a redundant presentation of the studied signal. For solving this issue, the Discrete Wavelet Transform (DWT) has been established, which scales and transforms wavelets in discrete stages. The DWT of a signal $f(n)$ with mother wavelet function $\psi[n]$ is represented as [23]:

$$DWT(x, y) = \frac{1}{\sqrt{x}} \sum_{n=-\infty}^{\infty} f[n].\psi\left(\frac{n-y}{x}\right) \qquad 3.3$$

The following equations express the detail and approximate coefficients at the first decomposition level:

$$A_1(n) = \sum_k h(k-2n)f(k) \qquad 3.4$$

$$D_1(n) = \sum_k g(k-2n)f(k) \qquad 3.5$$

where $h(n)$ and $g(n)$ respectively represents the low pass filter and high pass filter coefficients which are used to decompose $f(n)$ to A_1 and D_1 respectively. The signals obtained as an outcome of this decomposition are identical to the original signal, yet they represent distinct frequency bands.

3.3.2. Fault feature extraction

Feature extraction involves obtaining the feature vector during normal operation and fault events through DWT analysis. The wavelet coefficients are not directly employed as features so as to minimize the feature vector's dimensionality for each measurement. Consequently, statistic characteristics that represent the variations in these coefficients are computed [40]. Fault diagnosis must select relevant features that represent the input signal's characteristics. The data mining model for defect detection and diagnosis is then built using these features.

In the proposed scheme, pole and ground currents are employed for feature extraction. The signals are sampled at 100 kHz. After sampling, DWT is used to obtain detailed coefficients of current signals. The maximum value among the detailed coefficients, which provides critical information during transient events like faults, is further employed as an input feature in the network's training.

Feature extraction using DWT is performed in MATLAB software using the following program:

```
open('DCMG_model.slx');
sim('DCMG_model.slx');
currentP=current1;
currentG=current2;
[cP,LP]=wavedec(currentP,1,'db4');      % computes the wavelet transform of the given signal
[cG,LG]=wavedec(currentG,1,'db4');
coefP=detcoef(cP,LP ,1);           % extracts the detailed wavelet coefficients from the signal
coefG=detcoef(cG,LG,1);
p= max(coefP)                     % obtains the maximum value among the detailed coefficients
g= max(coefG)
```

3.3.3. Feature extraction results

Several simulations of the DCMG model are done to test the suggested technique by simulating different faults (PG and PP) and non-fault conditions under various configurations. Using DWT analysis, the feature vector is retrieved for various faults and non-fault occurrences. A general trend discovered in feature vector under various fault/non-fault cases is summarized in Table II and explained below:

i. *Pole to Ground (PG) fault:* With a pole-ground fault, events are simulated in various fault configurations (e.g., different fault resistances, locations, incident times, etc.), and it has been observed that the maximum value of the detailed coefficient is high for both pole and ground currents. Thereby, differentiating them from normal conditions and pole-to-pole faults.

ii. *Pole to Pole (PP) fault:* The maximum value of the detailed coefficient for the pole to pole faults simulated under various fault configurations (e.g., different fault resistances, locations, incident times, etc.) came out to be high for pole current and low for ground current; hence, are characteristic of PP faults in DC microgrid.

iii. *Normal Operation:* Under normal operating conditions (simulated for various operating modes under varied load variations), it has been observed that the maximum value of the detailed coefficients for both pole and ground currents is low, which is distinct from that of a faulty network. As a result, fault events may be distinguished from normal DCMG operations by comparing feature vectors.

Table II: Feature extraction results

State	**Maximum detailed coefficient of pole current**	**Maximum detailed coefficient of ground current**
Normal condition	Low (<1)	Low (~$10^{-12 \text{ to } -18}$)
Pole- to- ground fault	High (>2)	High (>0)
Pole-to-pole fault	High	Low

3.4. ANN FOR FAULT DETECTION AND IDENTIFICATION

The proposed fault detection and identification scheme uses an Artificial Neural Network (ANN) to distinguish between fault and non-fault cases. ANN compares features using soft criteria and may deduce the underlying nonlinear and complicated correlations between input and output data [41]-[42]. During the ANN training process, input data sets and output tags are given to the training algorithm. The error signal updates the ANN weights and biases through an iterative training process, bringing the network output closer to the targeted output.

3.4.1. Neural network architecture

The general artificial neural network (ANN) structure employed for fault detection and identification is shown in Fig.3.3. A three-layer feed-forward neural network comprising two input and three output nodes has been employed. Based on the classification accuracy, the number of nodes in the hidden layer are set to 10 and 12 for grid-connected and islanded mode respectively employing a trial-and-error approach.

The maximum value of detailed coefficients determined from pole and ground currents act as input to the ANN network. Three output classes defined for three cases include normal operation, pole-to-ground fault, and pole-to-pole fault. The scaled conjugate gradient algorithm has been used for training the artificial neural network.

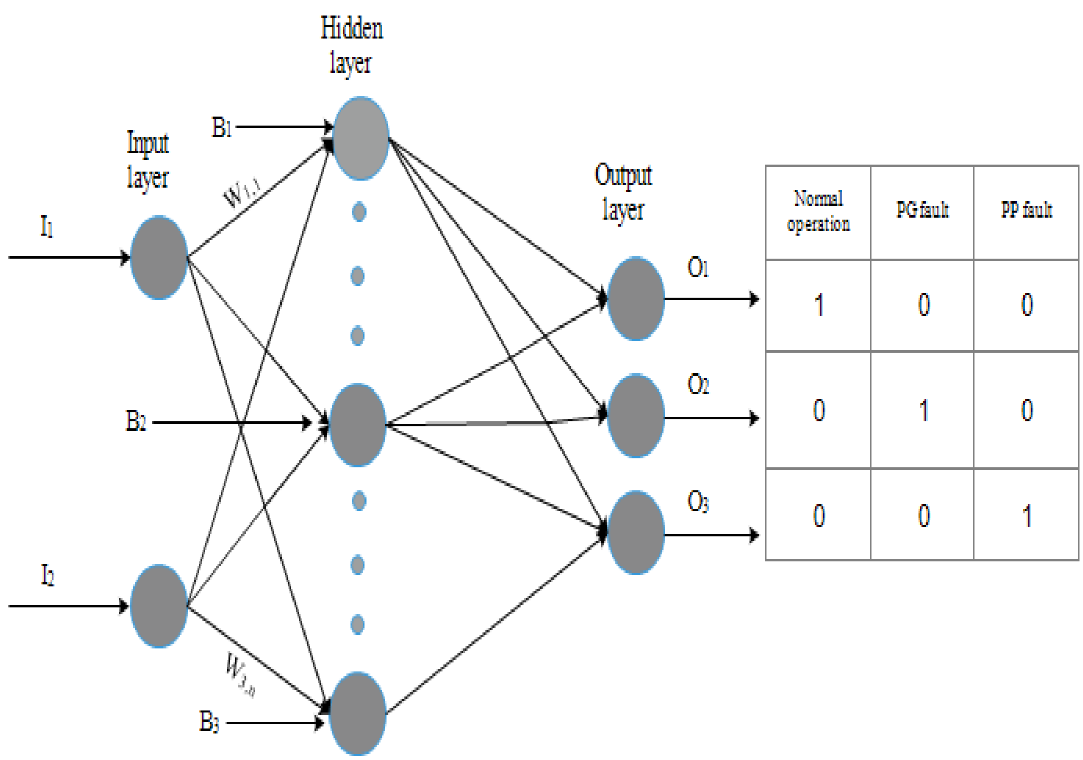


Fig. 3.3: General ANN structure for fault detection and classification

3.4.2. ANN training and testing

The ANN's learning parameters need to be trained offline. A substantial amount of previous information that reflects fault and non-fault occurrences under various operating situations is required for training the ANN using the supervised learning technique.

Table III: Configuration of simulated cases

State	Parameters	Specification			Count		
		Grid-connected mode	Islanded mode		Grid-connected mode	Islanded mode	
			PV with Battery	Only Battery		PV with Battery	Only Battery
Normal	Load change (%)	0, ±5, ±10, ±15, ±20, ±25, ±30, ±35, ±40, ±45, ±50, ±55, ±60	0, ±5, ±10, ±15, ±20, ±25, ±30, ±35, ±40, ±45, ±50, ±55, ±60	0, ±10, ±20, ±30, ±40, ±50, ±60	25	25	13
	SOC variation(%)	-	-	25,40,60,80	-	-	4
Fault	Fault location	Across load, across PV generator, after boost converter, across battery terminals, after buck-boost converter	Across load, across PV generator, after boost converter, across battery terminals, after buck-boost converter	Across load, across battery terminals, after buck-boost converter	5	5	3
	Fault resistance(Ω) (PG fault)	5,10,15,20,25, 30,35,40	5,10,15,20,25, 30,35,40	5,10,20,30,40	8	8	5
	Fault resistance(Ω) (PP fault)	0.1, 0.125, 0.15, 0.175, 0.2, 0.225, 0.25	0.1, 0.125, 0.15, 0.175, 0.2, 0.225, 0.25	0.1, 0.15, 0.2, 0.25	7	7	4
	Fault incident time (s)	0.5,1,1.5,2,2.5,3, 3.5	0.5,1,1.5,2,2.5	0.5,1,1.5	5	5	3
	SOC variation (%)	-	-	25,40,60,80	-	-	4
					550	400	376
Total cases					550+400+376= **1326**		

Moreover, the training data must have sufficient information to enable ANN parameter optimization for approximating system performance. Historical information or time-series simulations can be used to generate training data, which includes both fault and non-fault current measurements. MATLAB/Simulink is used to obtain training data by simulating the DCMG model under various fault conditions.

Fault simulations are performed using different types of faults, fault resistances, fault locations, and operating modes. Non-fault cases involving load switching under various operating modes have also been simulated and are listed in Table III. For ANN training and testing, a total of 1326 cases are simulated.

In a 3:1 ratio, the simulated data is divided into training and testing sets. ANN's learning parameters are trained using the training data set, whereas the testing data set is used to assess the machine learning model's classification accuracy.

CHAPTER 4
RESULTS AND DISCUSSION

This chapter includes the simulation results obtained from the DC microgrid under steady-state as well as faulty (pole-to-ground, pole-to-pole) conditions in both grid-parallel and grid-isolated modes. Further the results obtained from the ANN model for fault detection and identification have also been presented. In addition to this, the performance evaluation and accuracy computation of the proposed protection scheme using the confusion matrix and the F1-score for both grid-parallel and grid-isolated operating modes have also been discussed in this chapter. The results obtained show that the suggested protection method is precise, sensitive, and offers very high fault detection and identification accuracy for the DC microgrid.

4.1. DC MICROGRID SIMULATION RESULTS

In this study, the DC microgrid system consists of the utility grid, photovoltaic (PV), battery, and load. The PV generator, battery, and load are linked to the DC bus. The DCMG incorporates a radial topology with a 440 V DC nominal bus voltage. The Simulink model of the DCMG is developed employing MATLAB/Simulink.

To validate and assess the performance of the developed DC microgrid model, various case studies are considered. These include -PV with the battery connected to the main grid (grid-connected mode); PV with battery; and only battery (grid-isolated mode) supplying the load.

4.1.1. Grid-connected mode

In grid-connected mode, the load is fed through coordinated control of the PV array, grid, and battery. Here, PV and battery have been linked, and a voltage source converter (VSC) is used to synchronize them with the main grid. The simulation model of DCMG in grid-connected mode is given in the appendix in Fig.A1.

Fig.4.1- 4.3 respectively represents the power, voltage, and current for the main grid bus under steady-state conditions. Here, the load voltage is maintained constant at 440V as shown in Fig.4.5. Fig.4.4 depicts the VSC voltage, which corresponds to the DC-DC converter output voltage (440 V). Fig.4.6 represents the battery voltage which corresponds to about 160V.

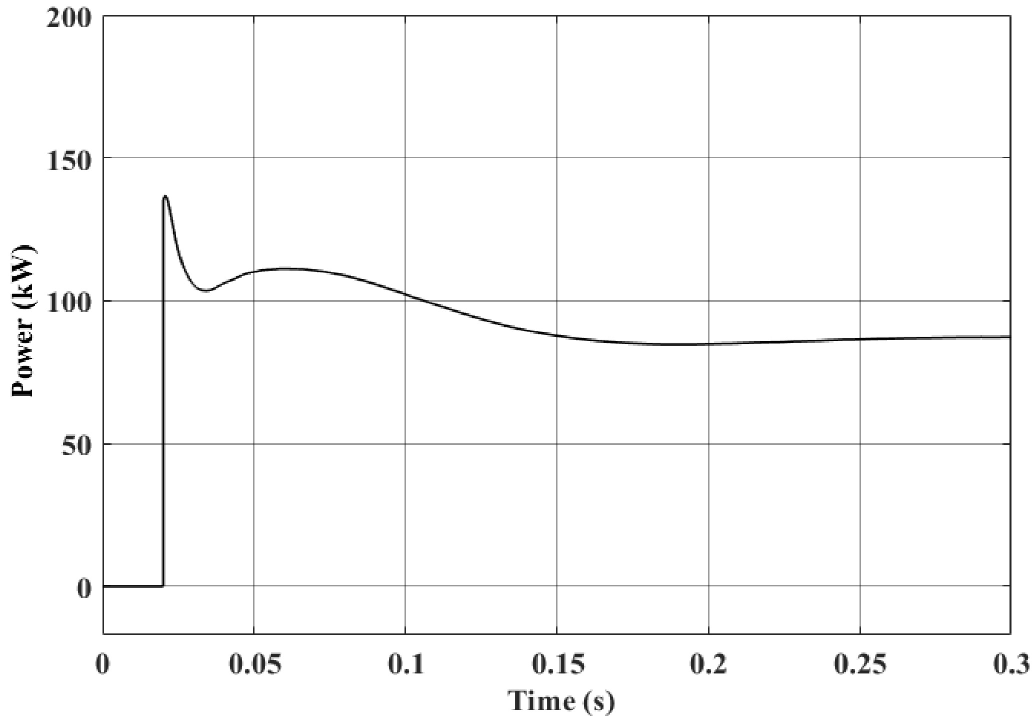


Fig. 4.1: Power for main grid bus

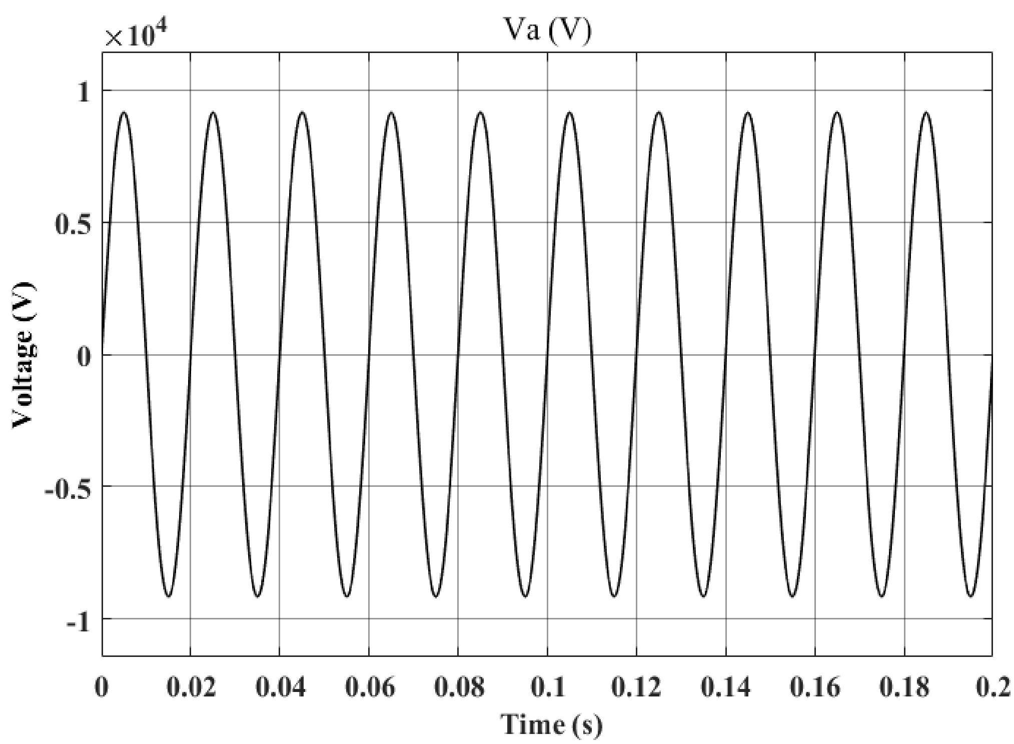


Fig. 4.2: Voltage for main grid bus

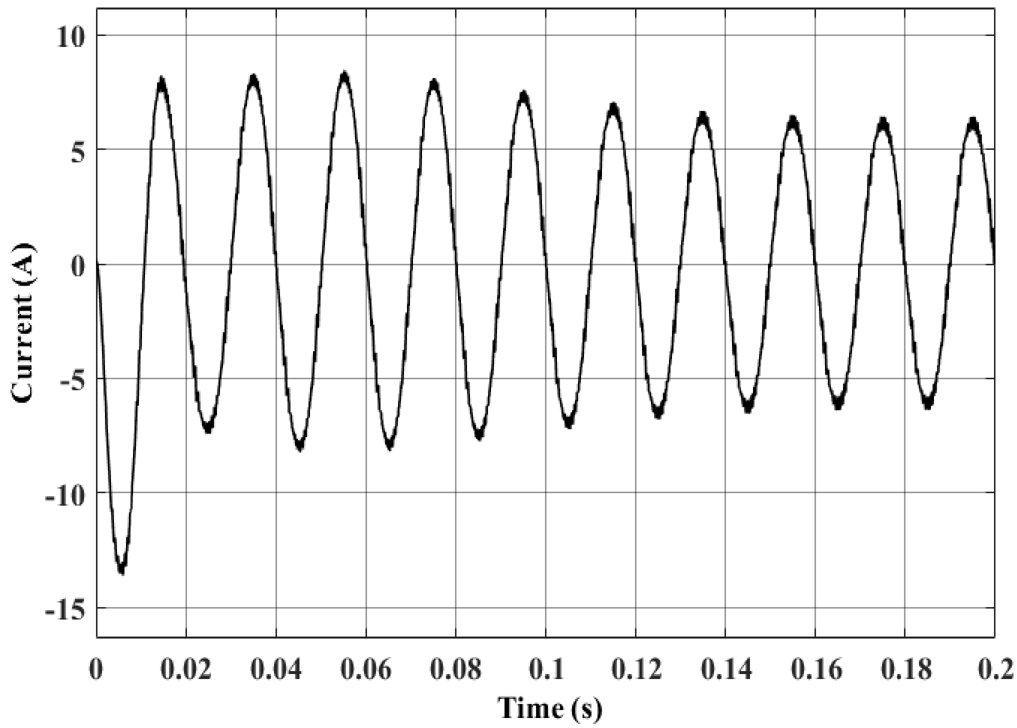


Fig. 4.3: Current for main grid bus

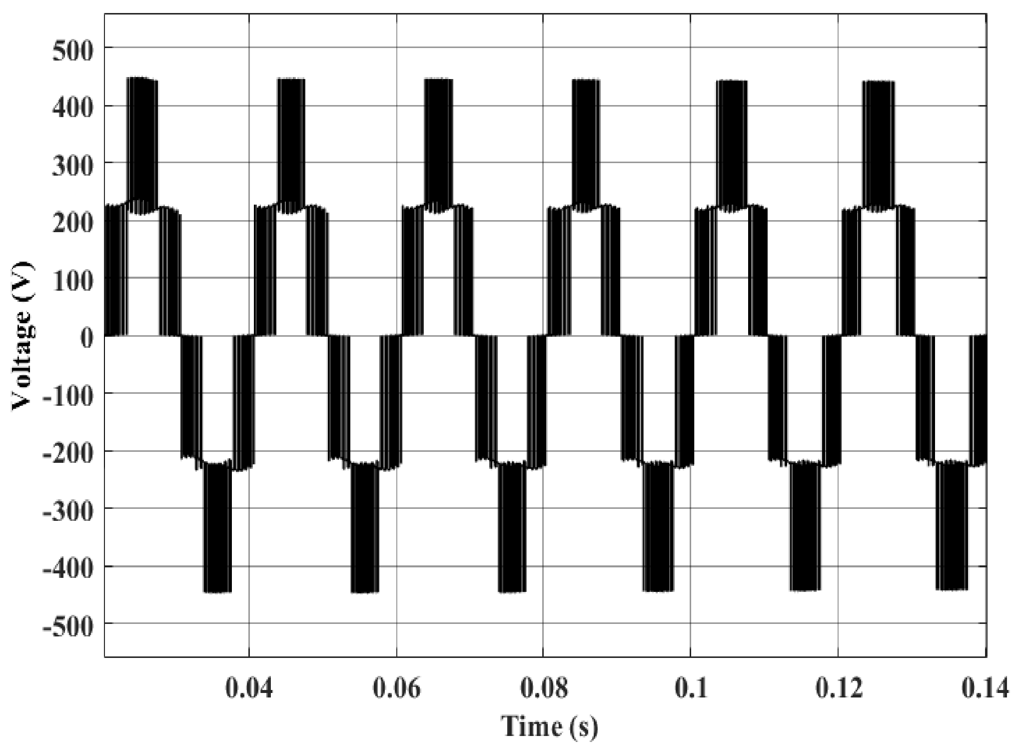


Fig. 4.4: Voltage of Voltage Source Converter (VSC)

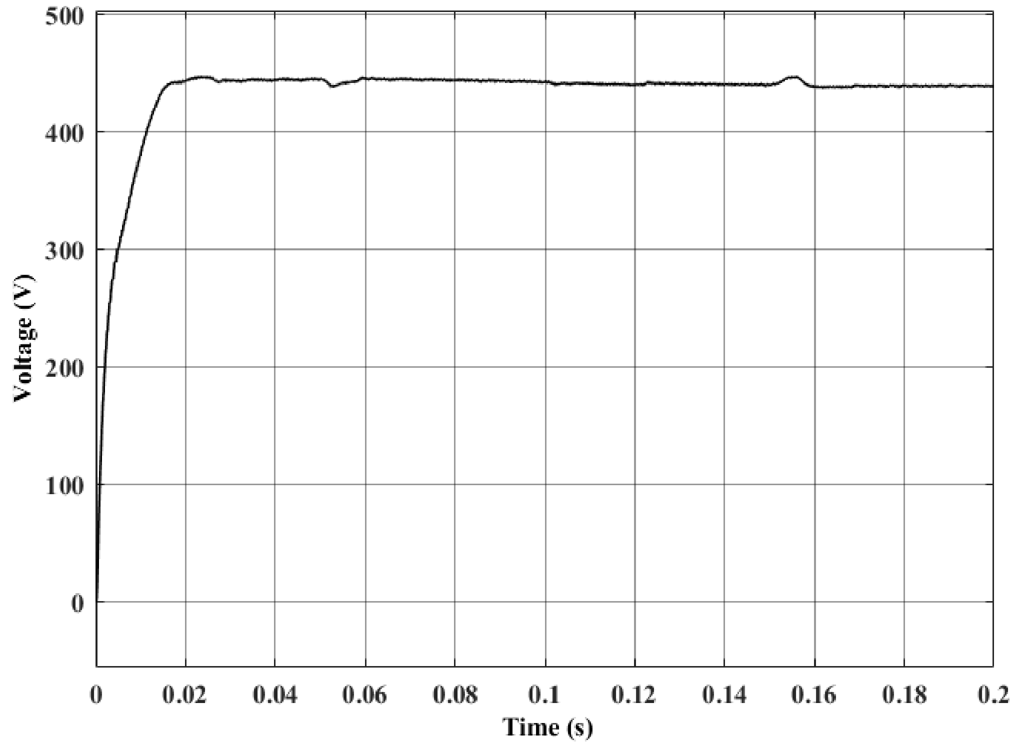


Fig. 4.5: Load voltage under grid-connected mode

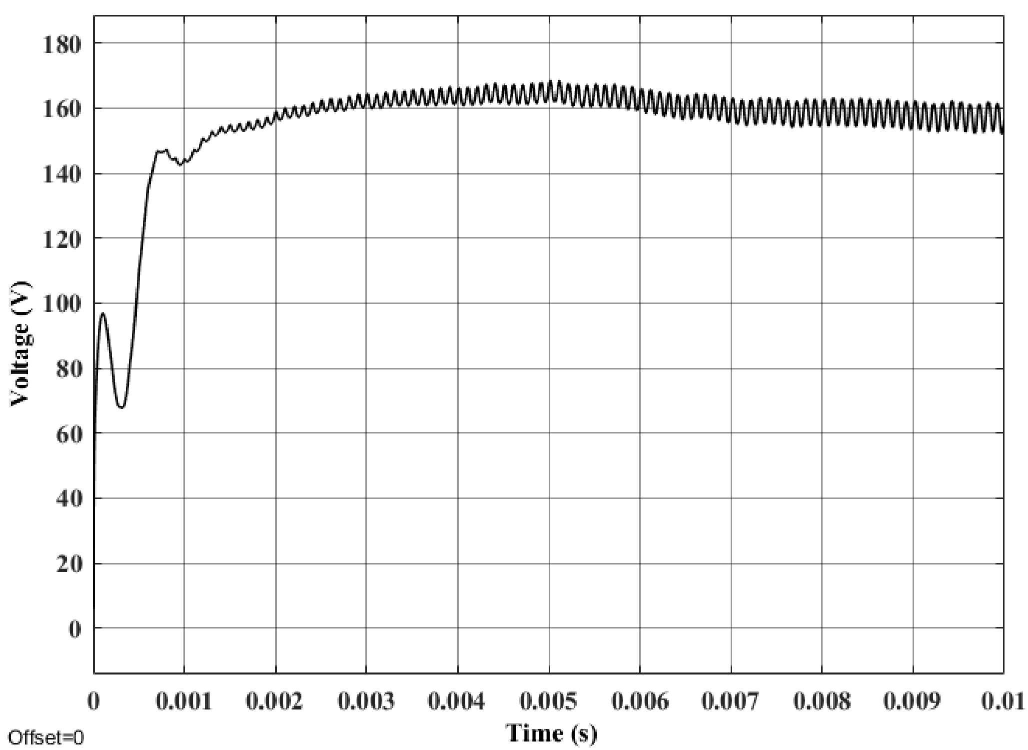


Fig. 4.6: Battery voltage under grid-connected mode

4.1.2. Islanded mode

In islanded mode, the DC microgrid is isolated from the main grid and functions autonomously with micro sources and load. The Simulink diagram of DCMG in the islanded mode is given in the appendix in Fig.A2. Operation of DCMG in islanded mode is further divided into two cases:

a. *PV with Battery:* Here, a PV array with battery energy storage systems (BESS) is employed to supply the load. Solar PV generates energy based on irradiation, shown in Fig.4.7. A part of this energy is used to charge the battery while the rest is used to power the load. Fig.4.8 shows the PV voltage under islanded mode. A significant reduction in PV voltage can be observed at t=0.5s, which is caused due to a drop in irradiance level at that instant. The PV current also tends to follow the irradiance level as seen in Fig.4.9. The PV and battery maintain the line current steady at around 160A as depicted in Fig.4.10. The battery SOC varies corresponding to the irradiance level as shown in Fig.4.11. As the irradiance drops, the battery discharges to power the load alongside the PV, and when the irradiance level is high, the battery charges by operating the bidirectional buck/boost converter in buck mode. Fig.4.12 represents the output voltage of the bidirectional buck-boost converter after being stepped up from 160V to 440V.

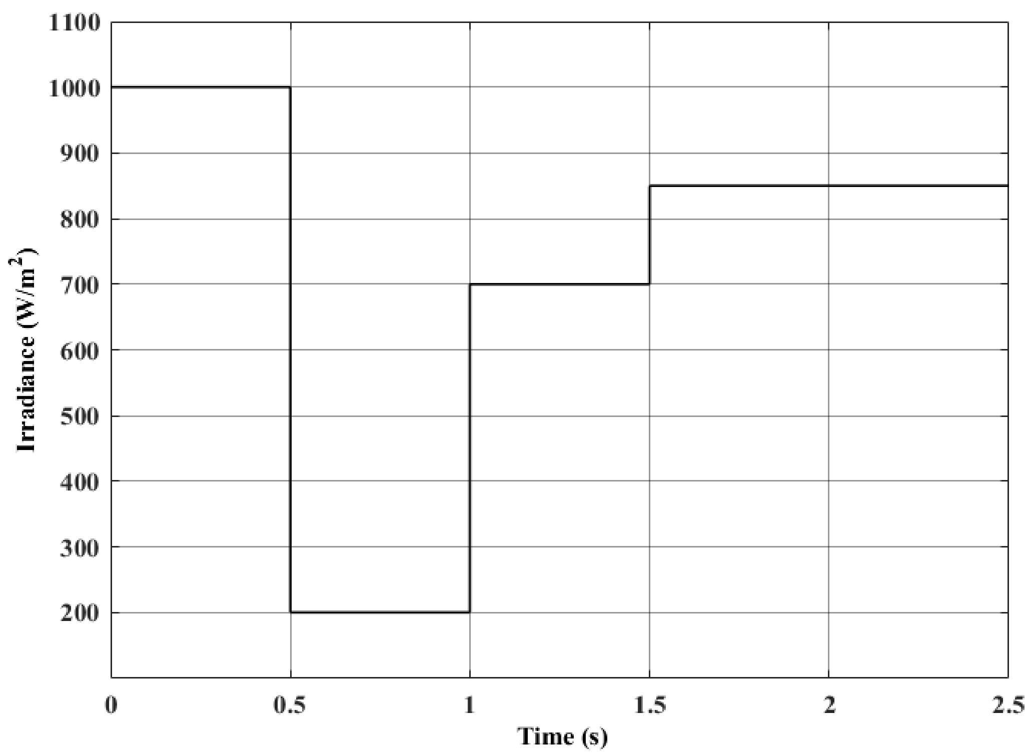


Fig. 4.7: Irradiance variation with time

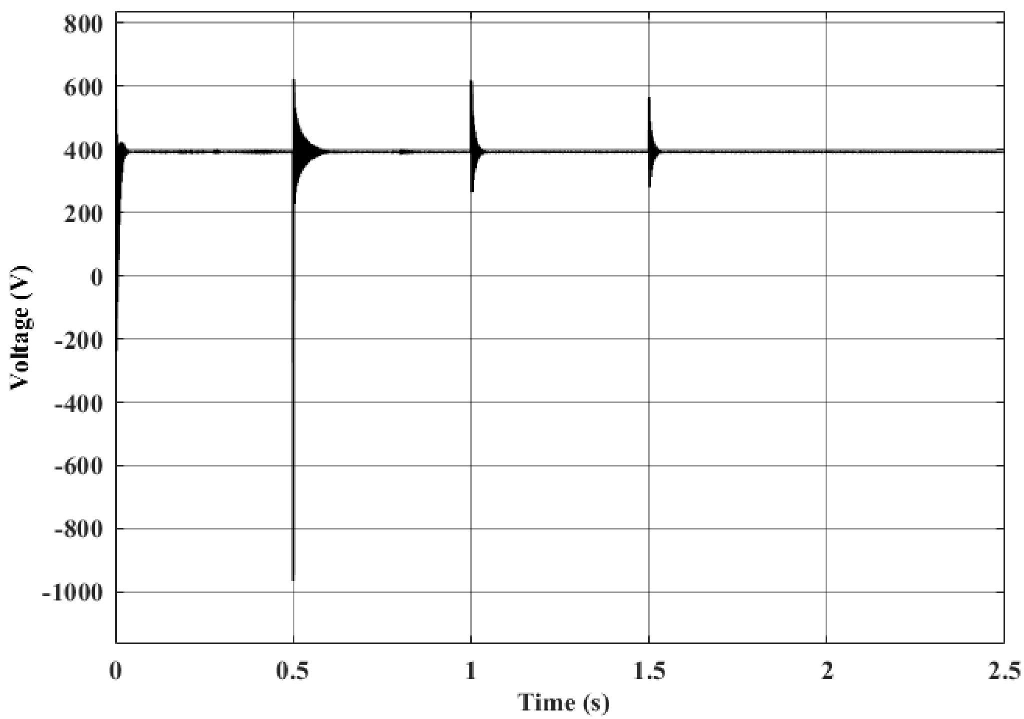


Fig. 4.8: PV voltage under islanded mode

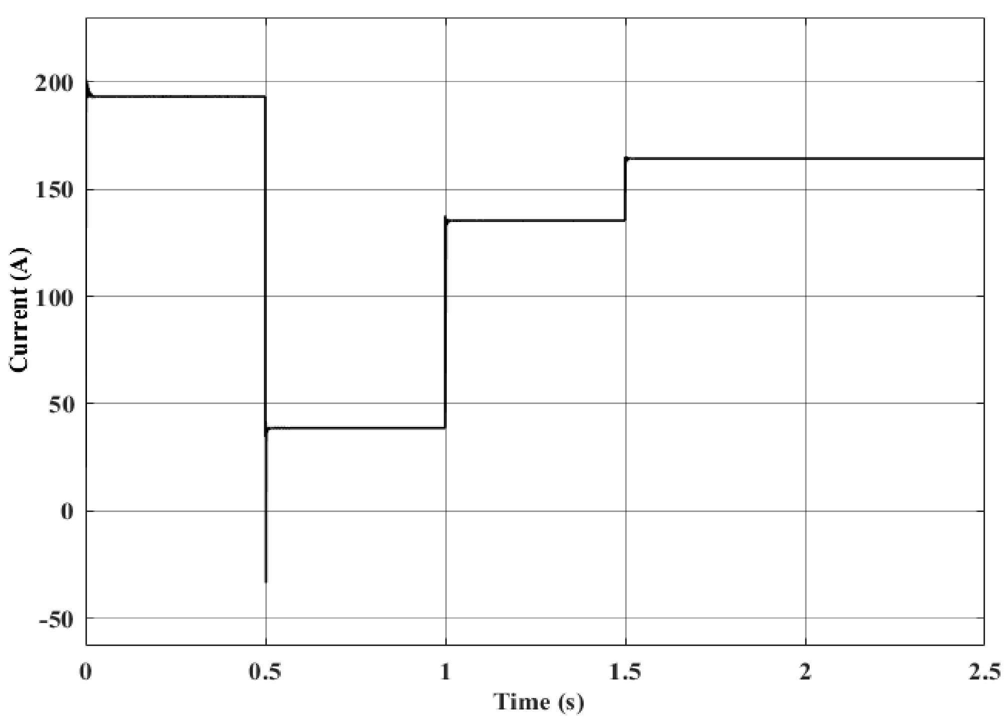


Fig. 4.9: PV current under islanded mode

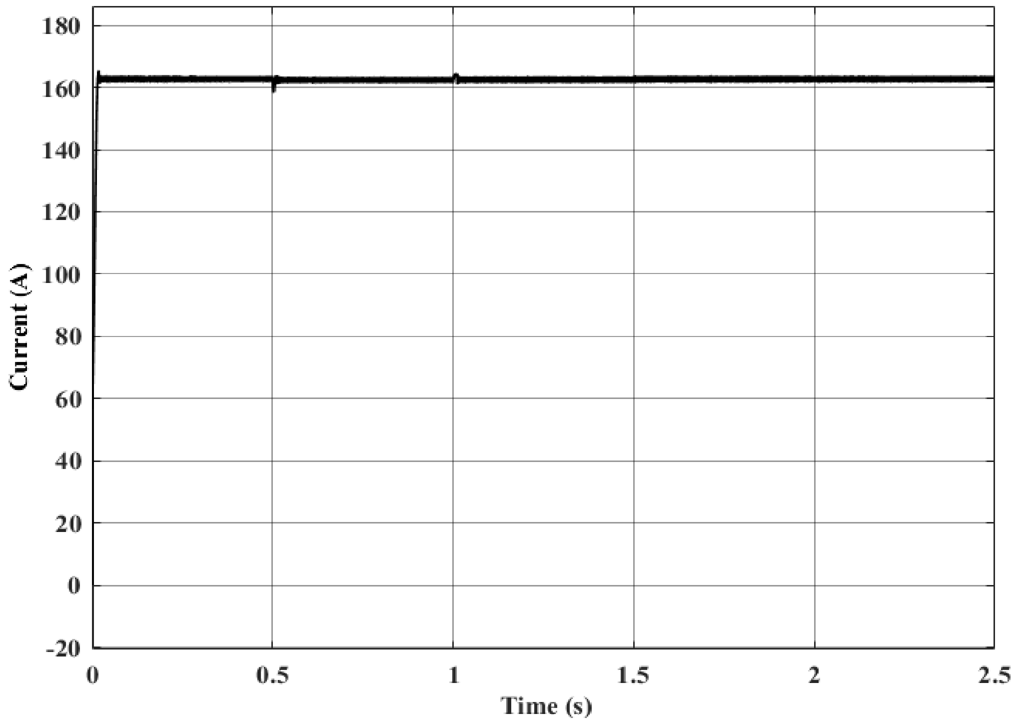


Fig.4.10: DC line current under islanded mode

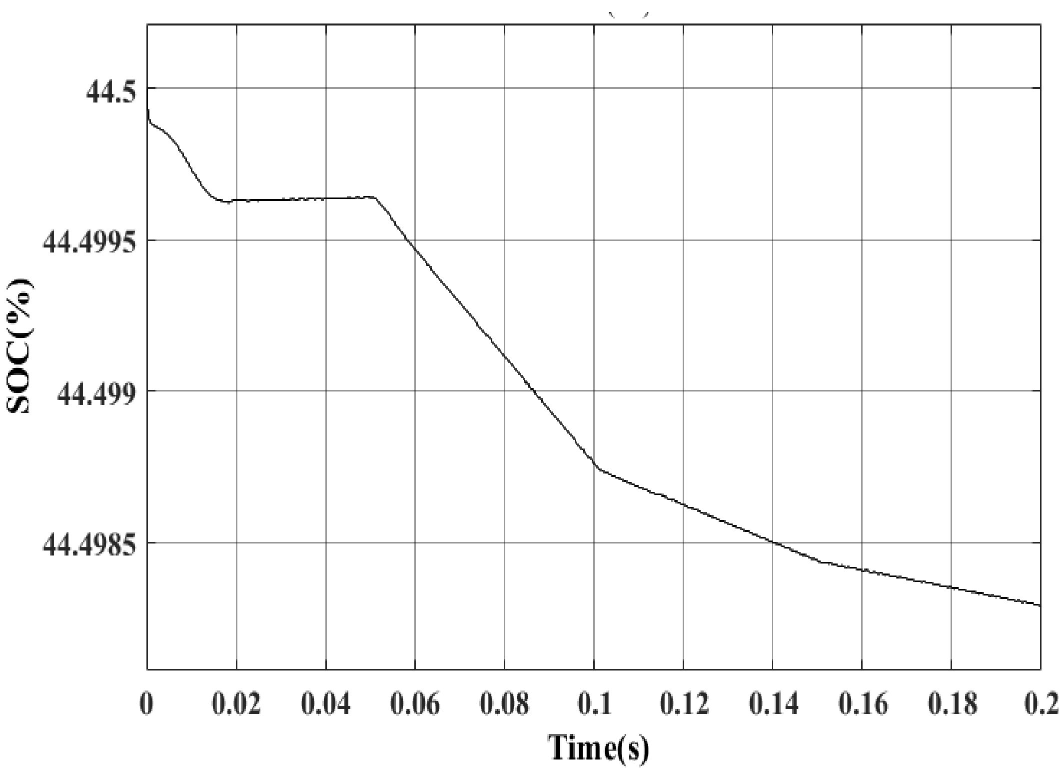


Fig. 4.11: Battery SOC under islanded mode

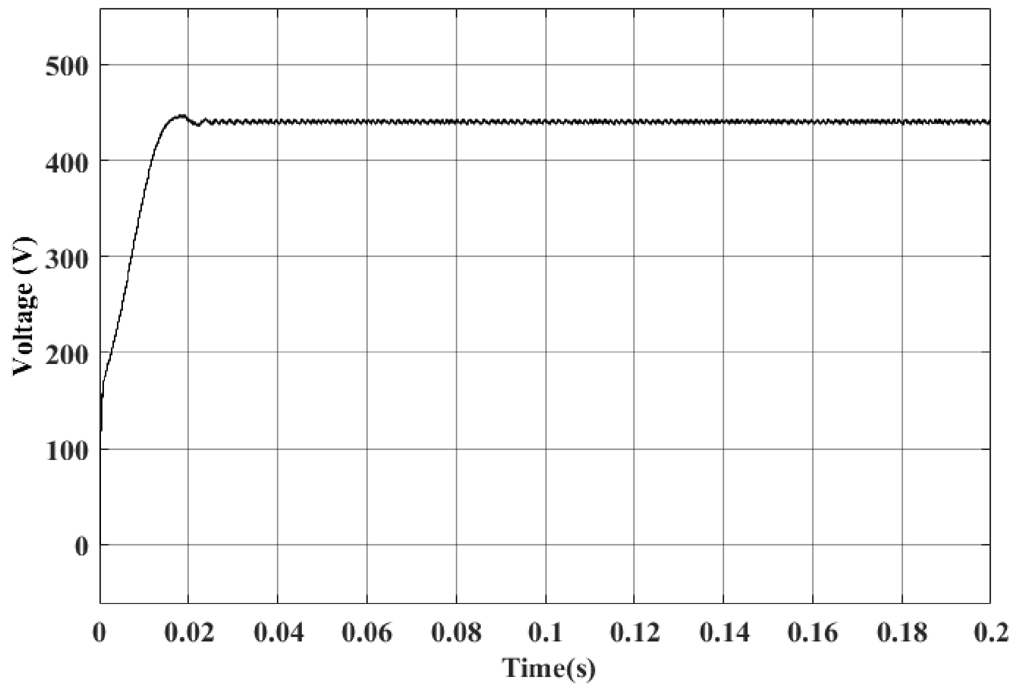


Fig. 4.12: Output voltage of the bidirectional buck-boost converter

b. *Only battery:* Here, the PV is disconnected from the system using a switch, and load is fed through the battery only, with a nominal voltage of 160V and battery capacity of 600 Ah with 60% SOC. Fig.4.13 represents the battery voltage which drops to about 140V due to dragging current from battery to supply the load. The load voltage is depicted in Fig.4.14 in which a drop of about 4% can be observed due to the line impedance.

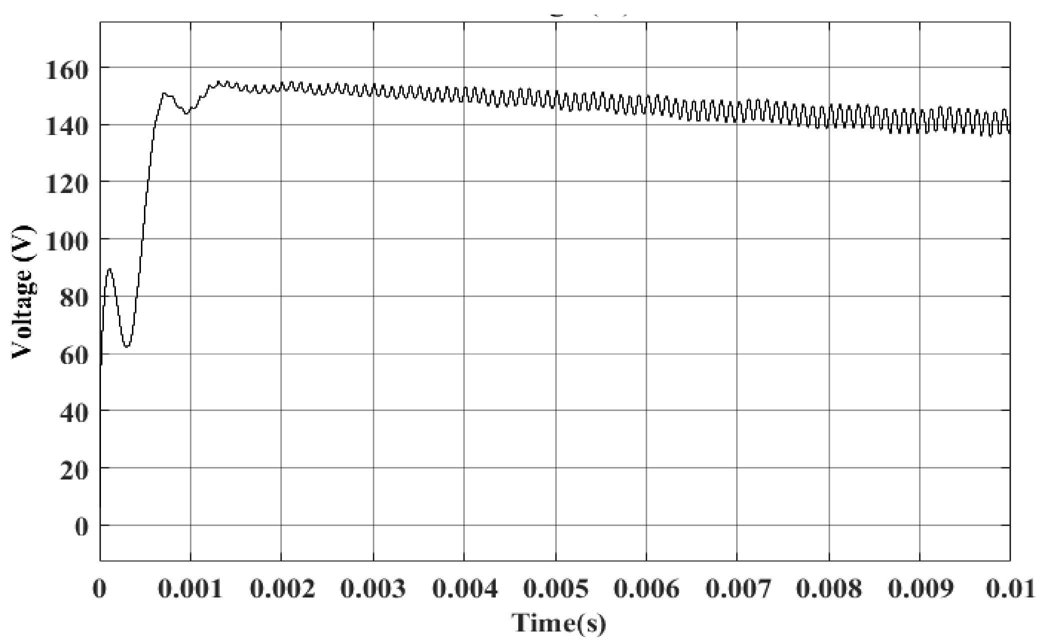


Fig. 4.13: Battery voltage

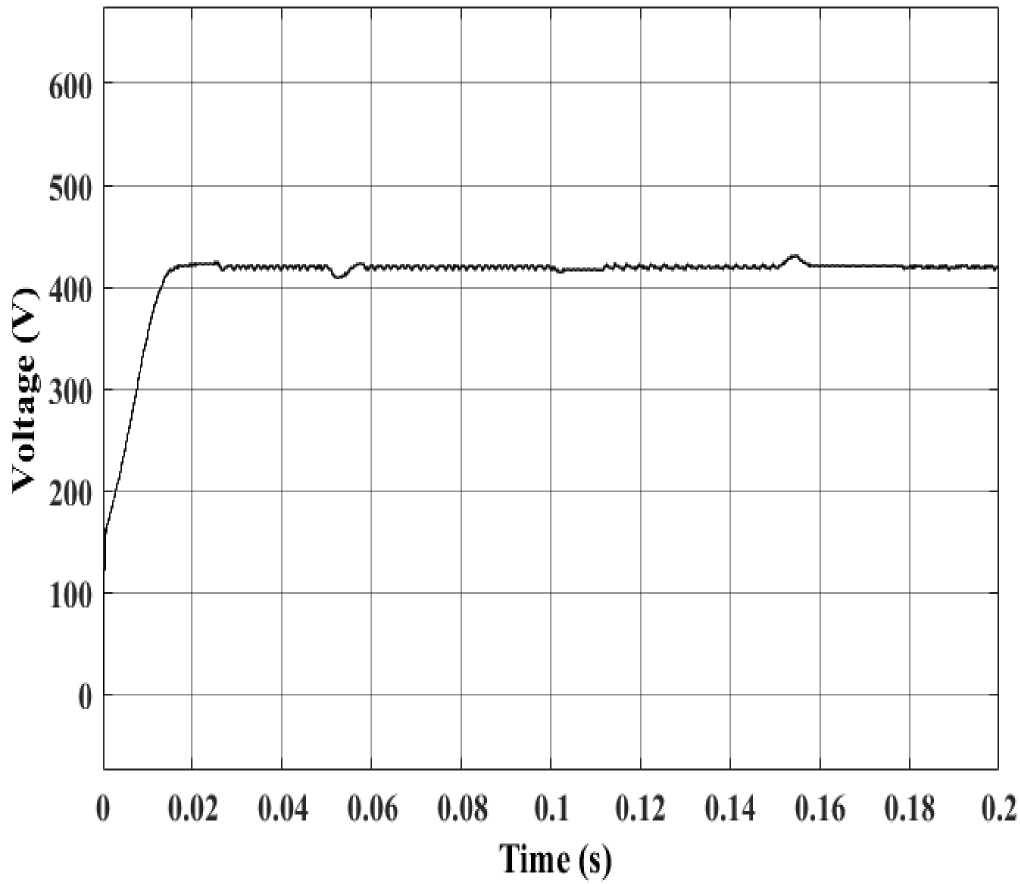


Fig. 4.14: Load voltage

4.2. FAULT ANALYSIS FOR DC MICROGRID

Short-circuit faults are regarded as the worst possible fault scenarios in a DC microgrid. The current of the system increases during these faults, depending on the type and location of the fault, and this current can harm the system. This section analyses the DC microgrid under grid-connected and islanded operation when PG and PP faults occur across the load. The results are shown in the figures below.

4.2.1. Grid-connected mode

a. *Pole-to-ground (PG) fault:* At t=0.15s, a PG fault with a fault resistance of 1Ω occurs across the DC bus. The DC load voltage drops whenever the fault arises as shown in Fig.4.15. In addition, Fig.4.16 represents the grid side currents that increase rapidly and attain a stable state after t=3.5s. The voltage of VSC decreases during the fault and a sharp increase in the fault current can also be observed as depicted in Fig.4.17 and Fig.4.18 respectively.

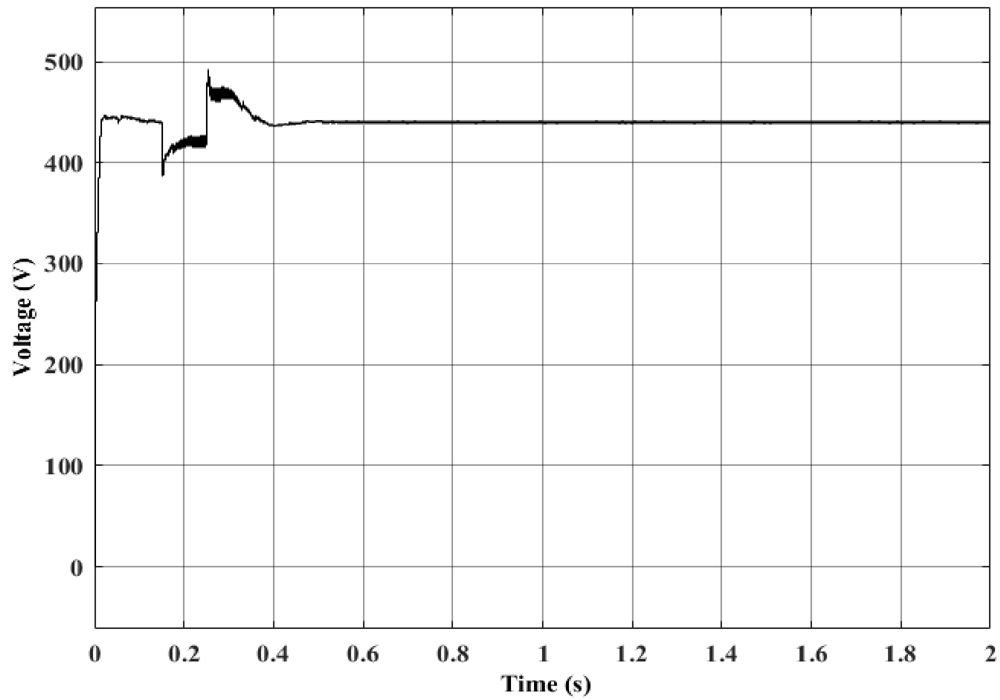


Fig. 4.15: Load voltage during PG fault under grid-connected mode

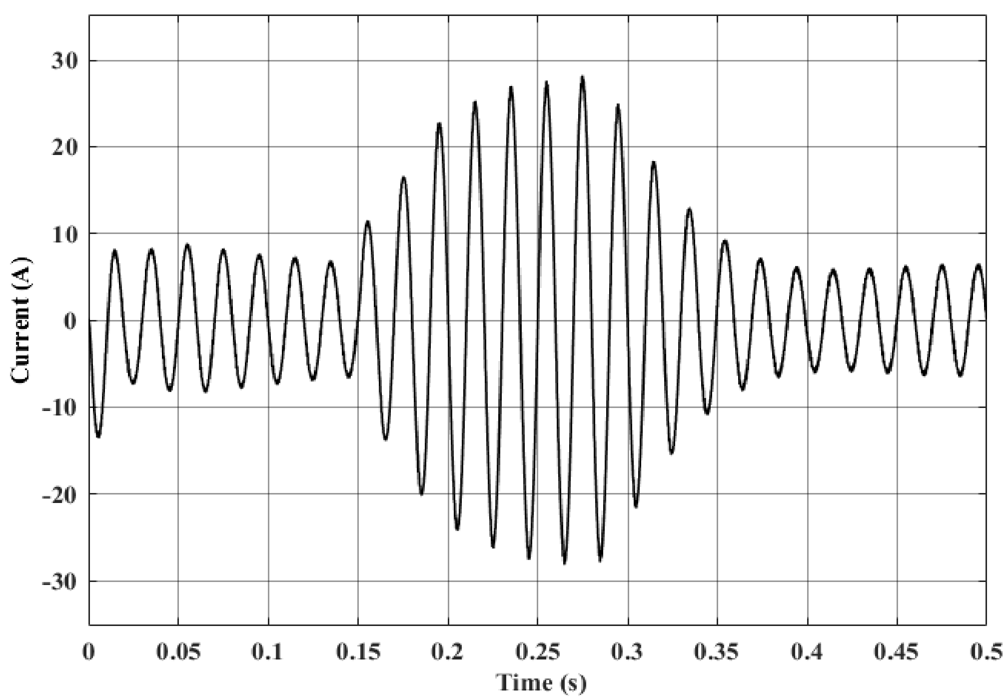


Fig. 4.16: Current of main grid bus during PG fault

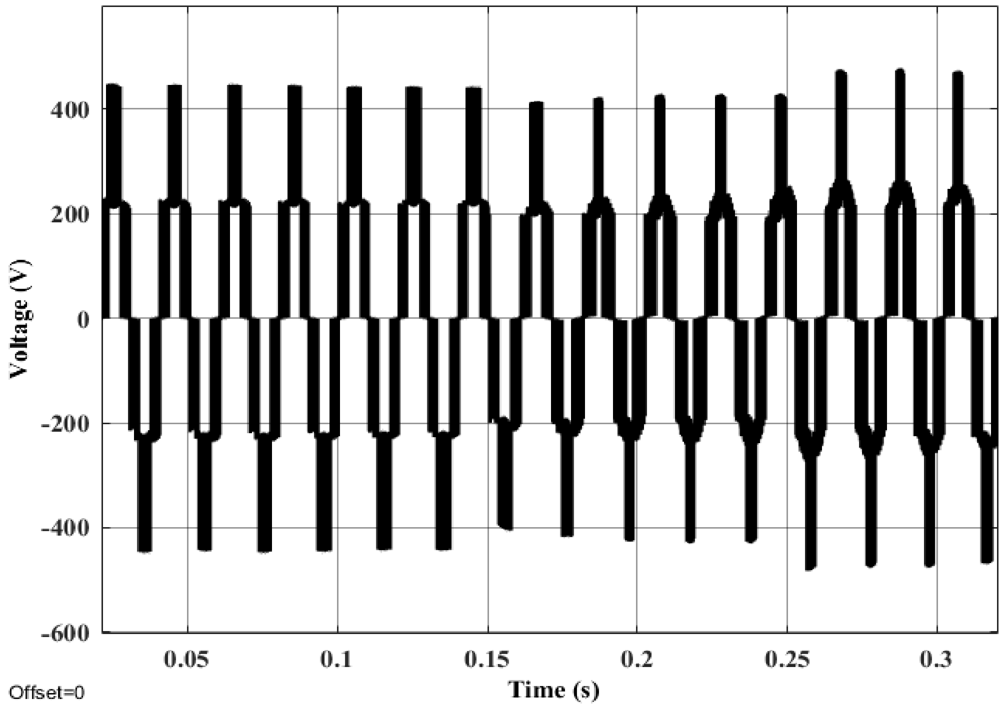


Fig. 4.17: Voltage of VSC during PG fault

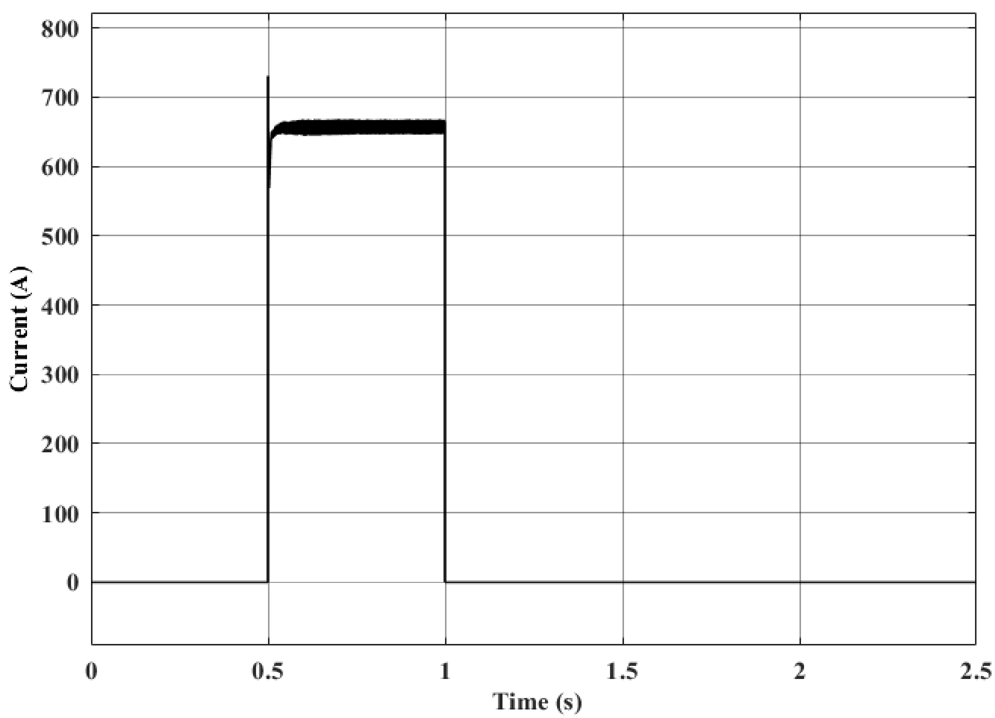


Fig. 4.18: Fault current during PG fault under grid-connected mode

b. *Pole-to-pole (PP) fault*: At t=0.15s, PP fault is created at the load end with a fault resistance of 0.1Ω. It can be observed that the load voltage drops significantly during the fault as shown in Fig.4.19. Also, the grid side currents increase rapidly and attain a stable state after t=3.5s as depicted in Fig.4.20. Fig.4.22 represents a sharp spike in the fault current at the fault instant. The voltage of VSC also decreases during the fault as shown in Fig.4.21.

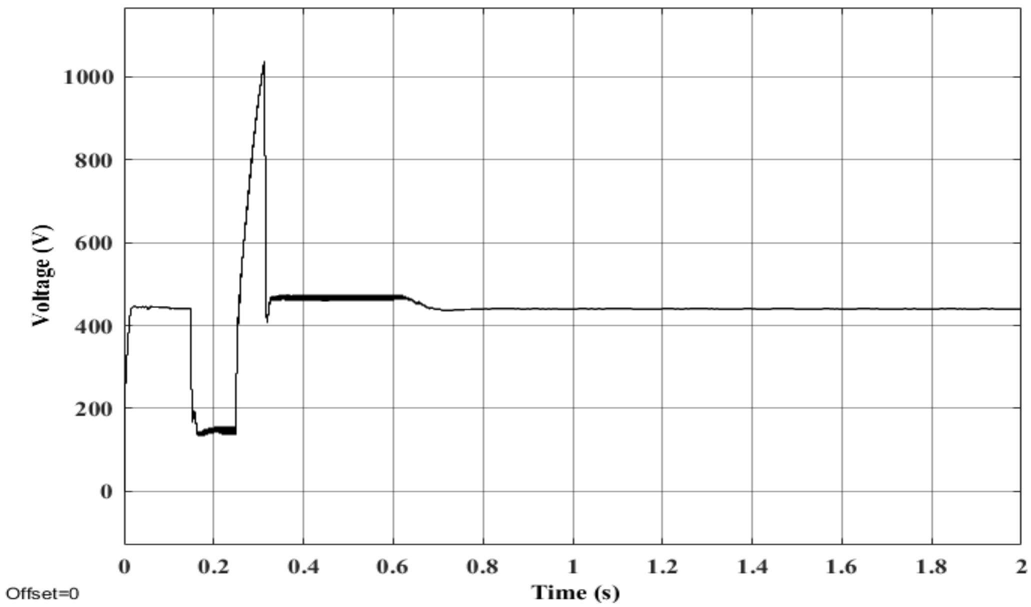


Fig. 4.19: Load voltage during PP fault under grid-connected mode

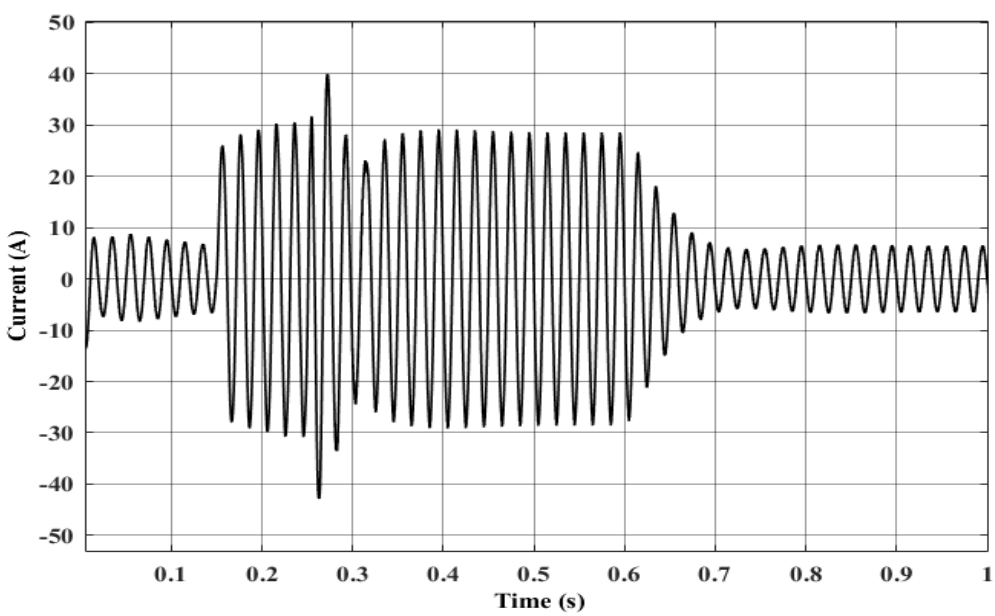


Fig. 4.20: Current of main grid bus during PP fault

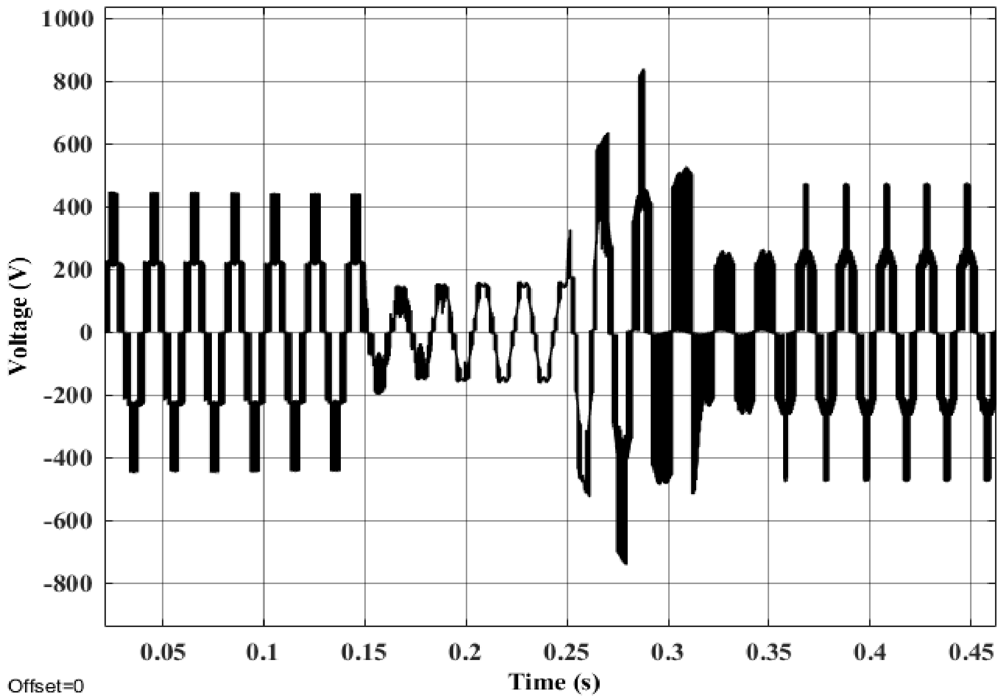


Fig. 4.21: Voltage for VSC during PP fault

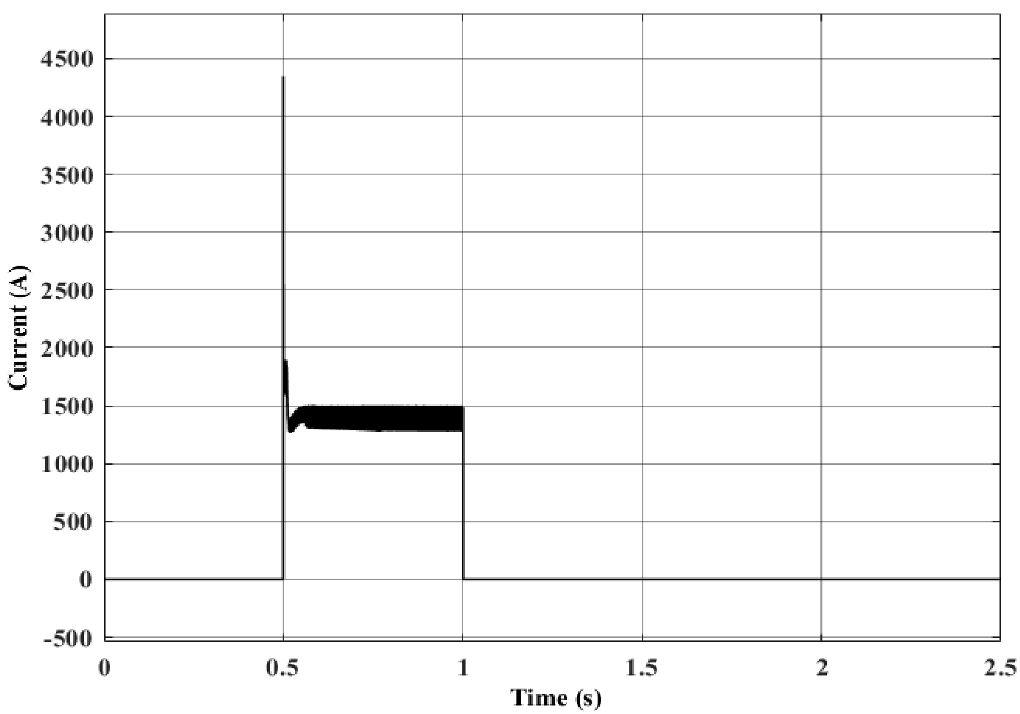


Fig. 4.22: Fault current during PP fault under grid-connected mode

4.2.2. Islanded mode:

a. *Pole-to-ground (PG) fault:* A PG fault with $R_f=1\Omega$ is created across the load at 0.5s. The load voltage drops to 374.6 V and the DC line current surges to 519.4A approximately as shown in Fig.4.23 and Fig 4.24 respectively. Fig.4.25 and Fig.4.26 respectively represent the significant drops in battery and PV voltage due to the fault. At t=1s, the fault is eliminated and the system restores to a steady state.

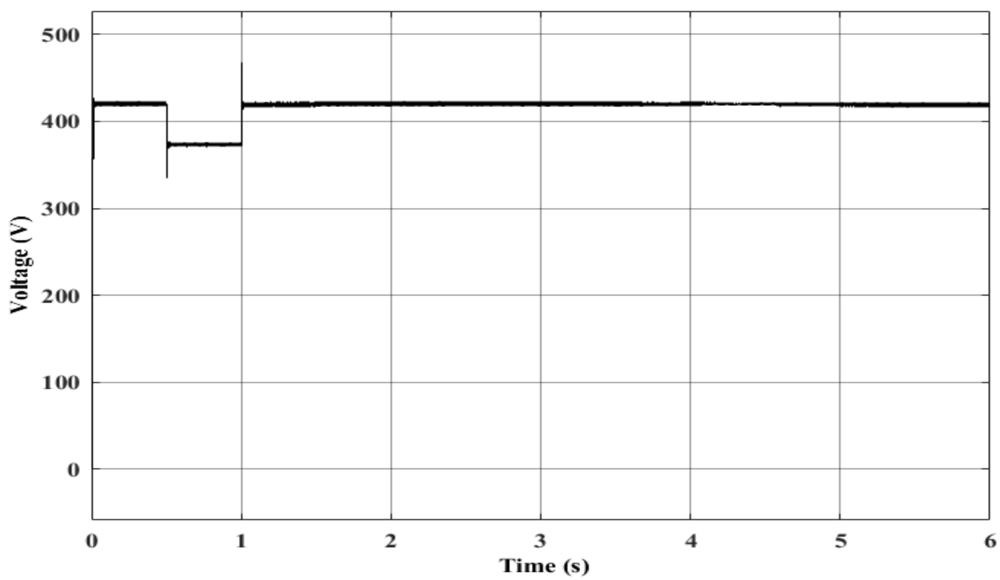


Fig. 4.23: Load voltage during PG fault under islanded mode

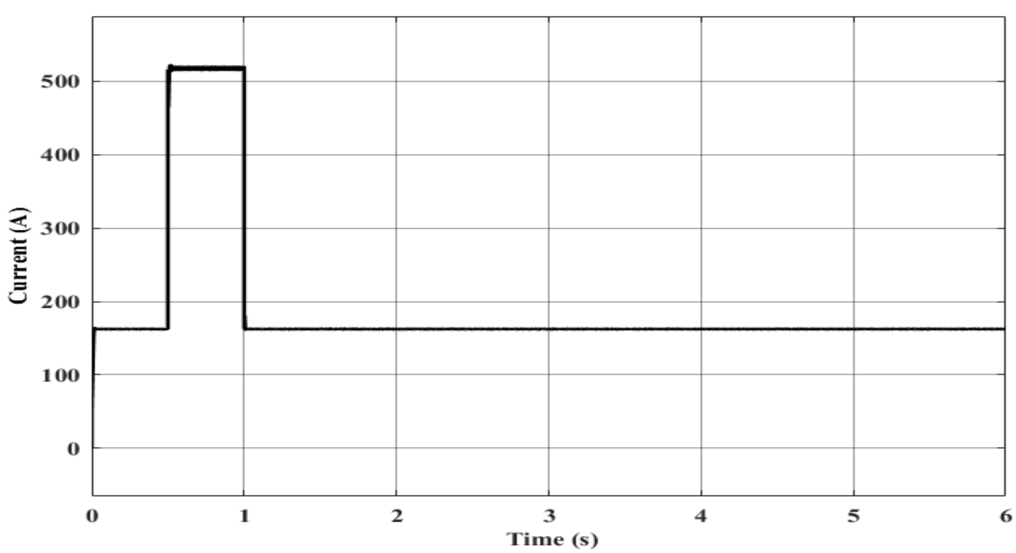


Fig. 4.24: DC line current during PG fault under islanded mode

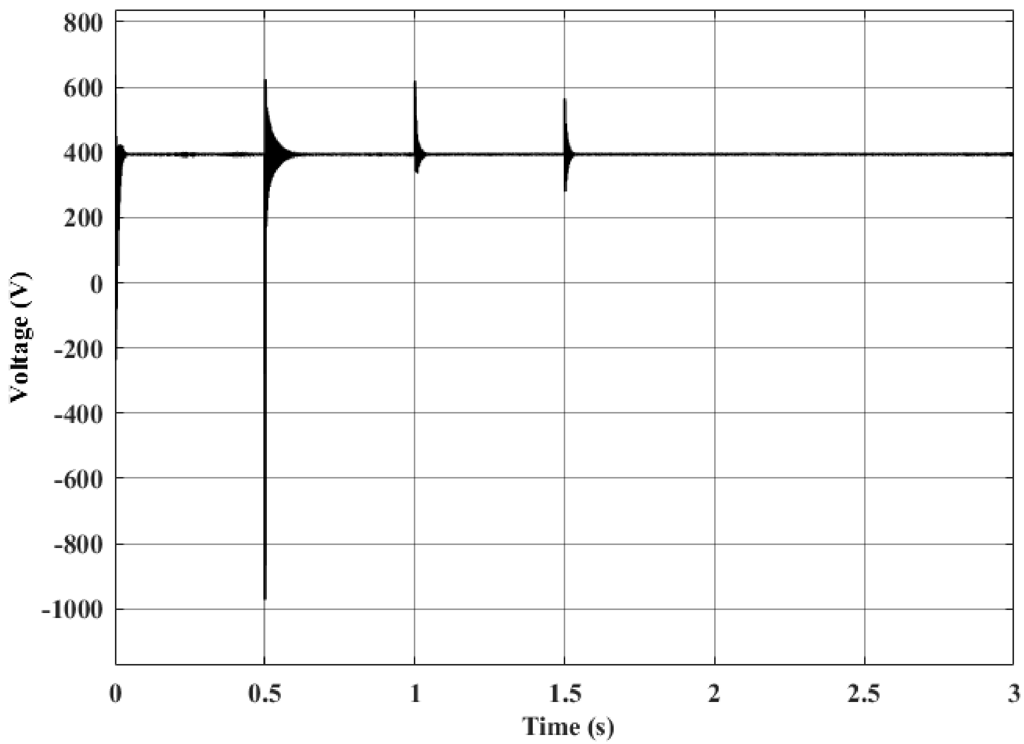


Fig. 4.25: PV voltage during PG fault under islanded mode

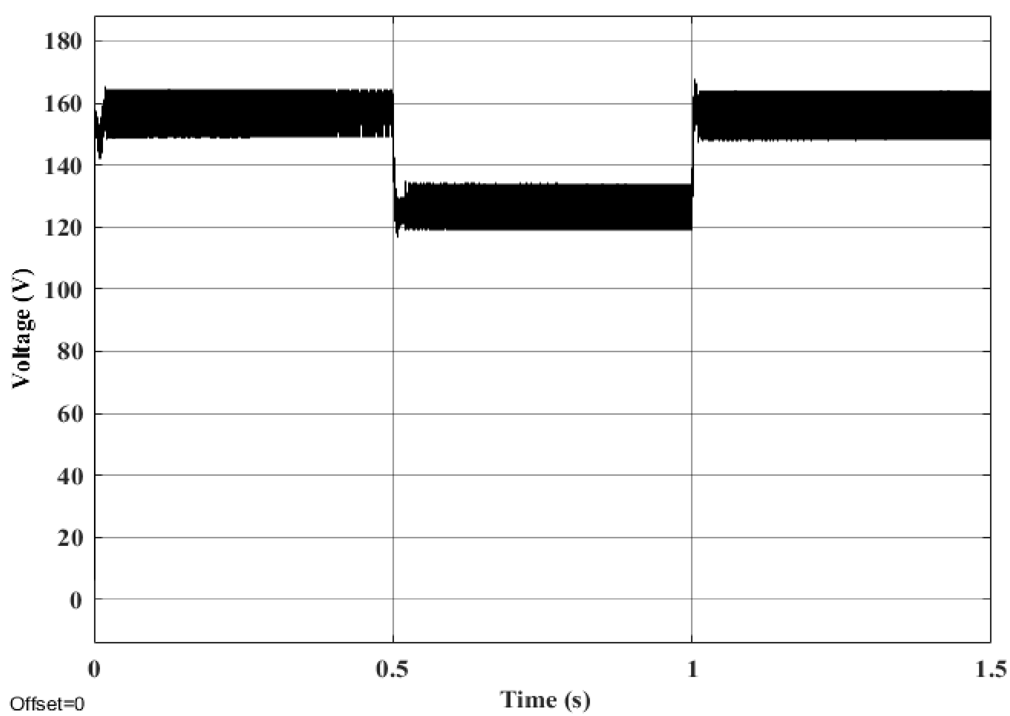


Fig. 4.26: Battery voltage during PG fault under islanded mode

b. *Pole-to-pole (PP) fault:* At t=0.5s, PP fault is created at the load end with a fault resistance of 0.1Ω. Fig.4.27 denotes the load voltage which decreases to about 34.61 V during fault. A similar trend can be seen for PV voltage as shown in Fig.4.28. Since PP faults are usually low impedance faults, there occurs a current spike of about 1800A during fault and a sharp increase in the battery output current can also be seen in Fig.4.29 and Fig.4.30 respectively. The system restores to a steady state after a certain transient period.

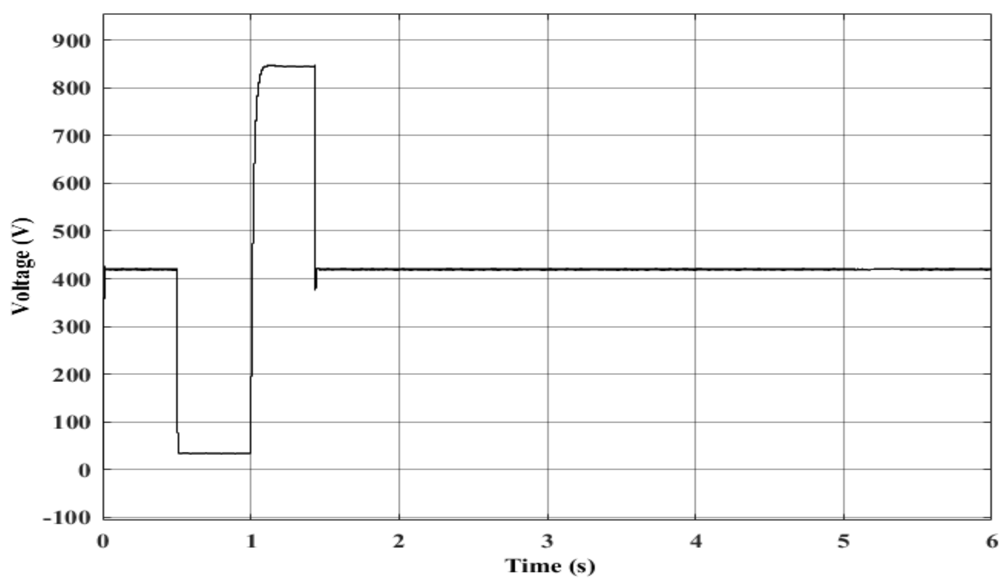


Fig. 4.27: Load voltage during PP fault under islanded mode

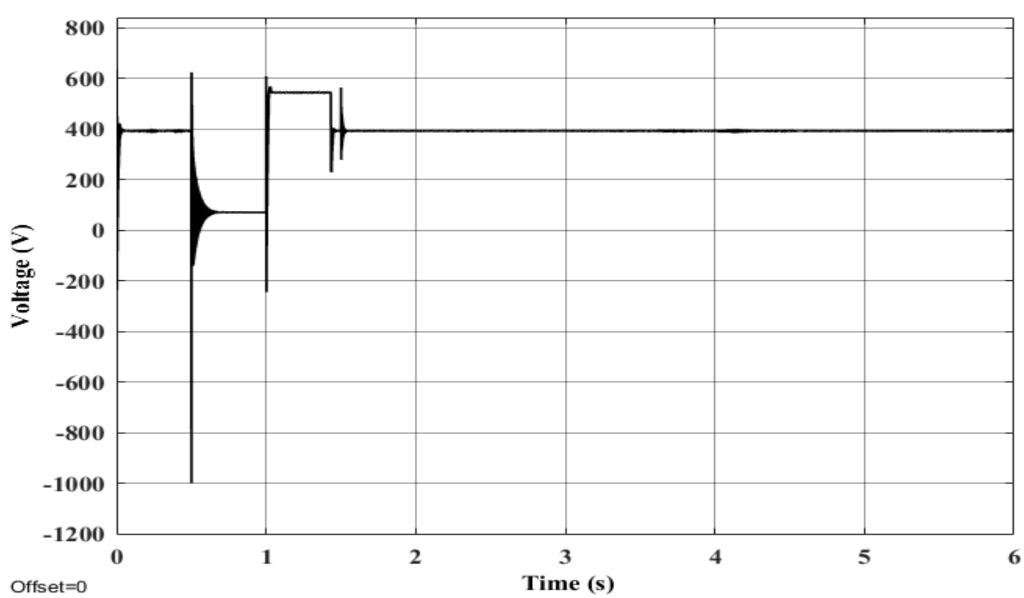


Fig. 4.28: PV voltage during PP fault under islanded mode

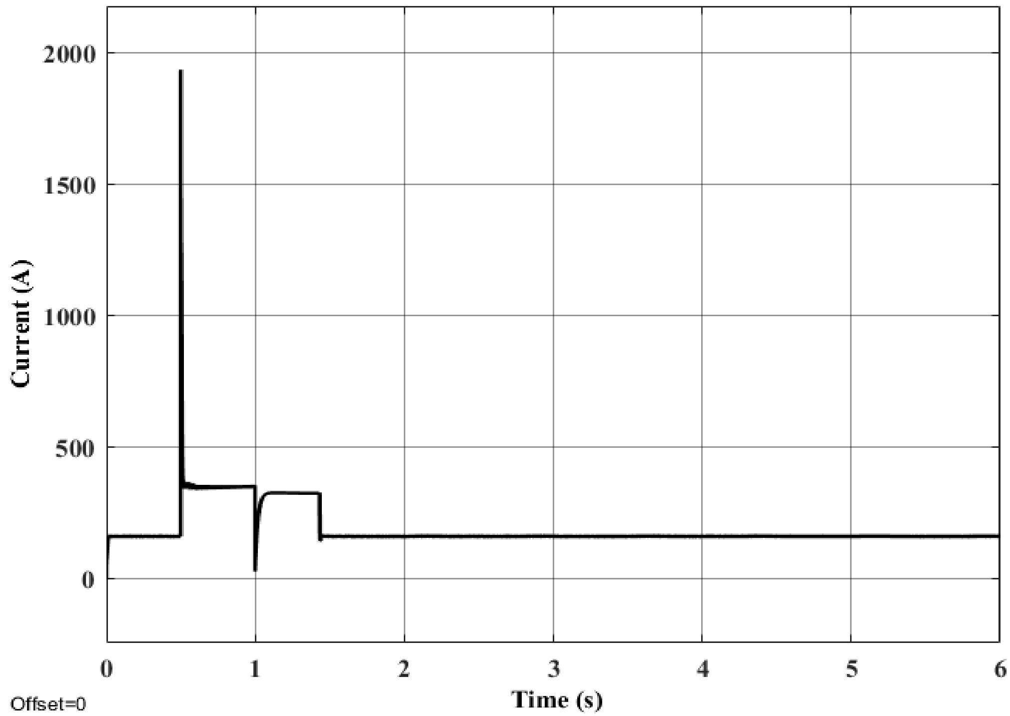


Fig. 4.29: DC line current during PP fault under islanded mode

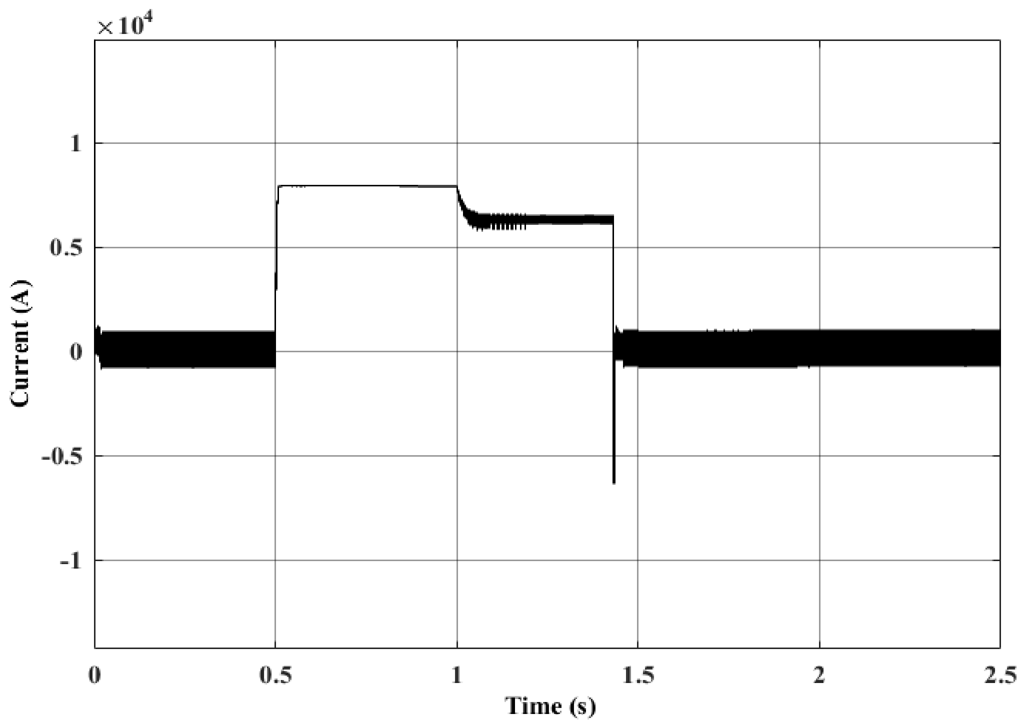


Fig. 4.30: Battery current during PP fault under islanded mode

4.3. RESULTS FOR FAULT DETECTION AND IDENTIFICATION USING ANN MODEL

To assess the suggested fault detection and identification method's performance during various fault and no-fault scenarios, a total of 1326 test cases are simulated in MATLAB/Simulink. The dataset is created by altering the load and introducing different faults (PG, PP) on the DC microgrid.

In a 3:1 ratio, the simulated data is divided into training and testing sets. The artificial neural network (ANN) model is trained with the training data set, whereas the testing data set assesses the machine learning model's classification accuracy. The developed ANN model assists the system in making the right decision about whether or not there is a fault and which type of fault occurred.

4.3.1. Grid-connected mode

Fig.5.1 shows the model of a trained Artificial Neural Network (ANN) system which detects and classifies the various types of DC faults. The developed ANN model is tested and examined in a case study with a pole-to-pole (PP) fault across the boost converter under grid-connected conditions as depicted in Fig.5.2.

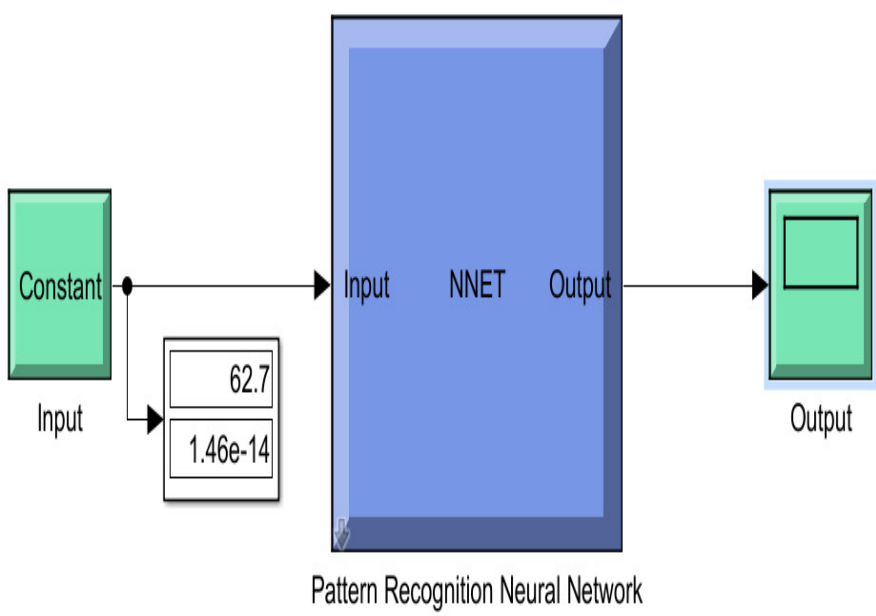


Fig. 5.1: Model obtained after consecutive ANN training under grid-connected mode

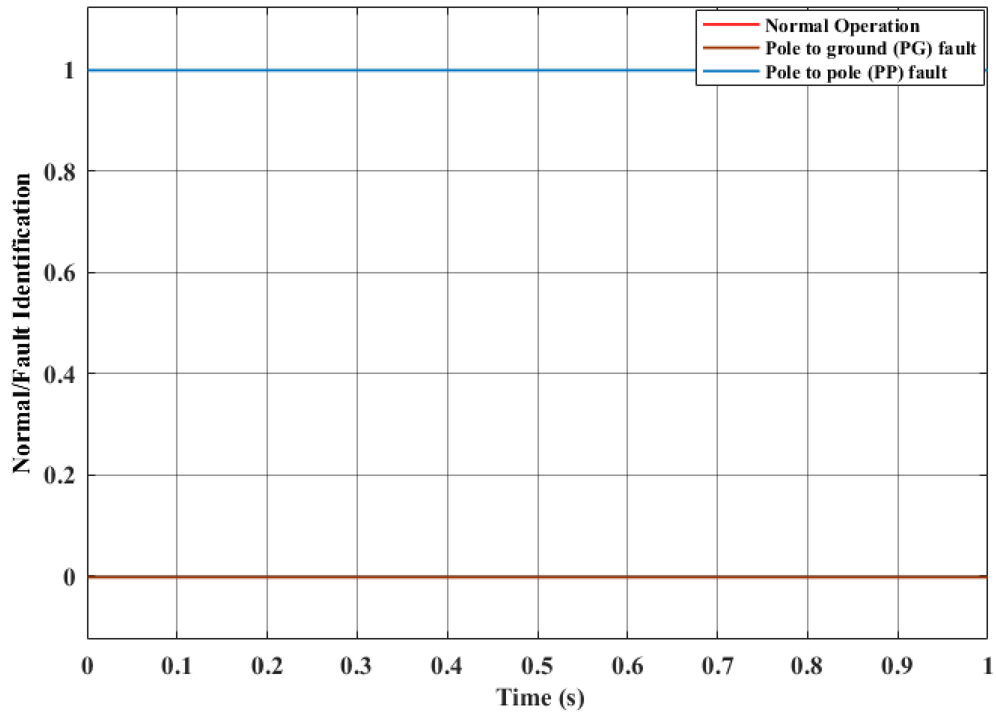


Fig. 5.2: PP fault identification using ANN under grid-connected mode

4.3.2. Islanded mode:

In a case study, under islanded operating mode, an ANN model, as shown in Fig.5.3, is tested and investigated using a PG fault across the PV generator. Fig.5.4 represents the output obtained from the ANN model which indicates the occurrence of PG fault.

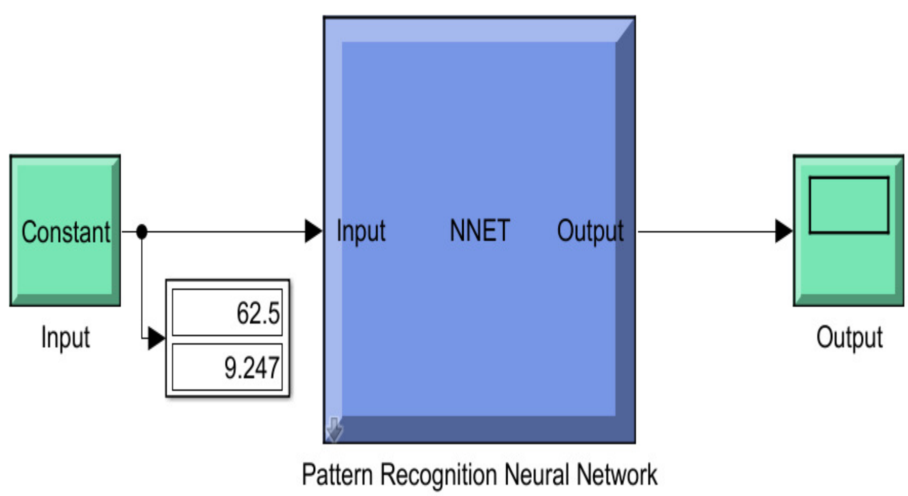


Fig. 5.3: Model obtained after consecutive ANN training under islanded mode

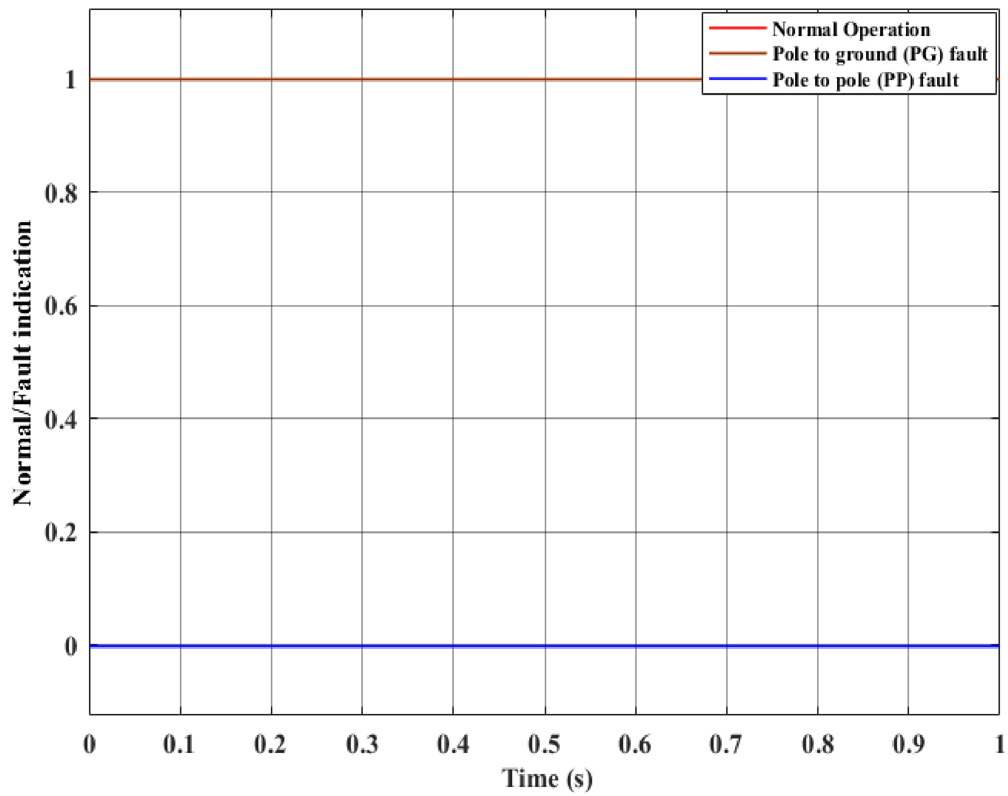


Fig. 5.4: PG fault identification using ANN under islanded mode

4.4. PERFORMANCE EVALUATION AND ACCURACY COMPUTATION OF PROPOSED SCHEME

This section covers a numerical evaluation of the suggested fault detection/identification technique's performance. To evaluate the scheme's efficiency, the F1-Score and confusion matrix has been constructed. Fig.5.5 and Fig.5.6 represent the confusion matrix, which provides a visual representation of the ANN's efficiency in fault detection and identification for grid-parallel and grid-isolated operating modes respectively. It shows the model's accuracy with respect to true cases and the trained model's prediction. Normal operation, pole-to-ground (PG) faults, and pole-to-pole (PP) faults are represented by classes 1, 2, and 3 respectively.

The diagonal cells represent the accurately classified cases, whereas the cases that are misclassified can be seen in off-diagonal cells. The overall classification accuracy and error are displayed in the bottom rightmost cell.

The F1-score, with a maximum score of 1, is a metric for evaluating the performance of machine learning-based methods. Equation 4.1 shows the mathematical expression for computing the F1-score [22].

$$F1\ score = \frac{2*Precision*Recall}{Precision + Recall} \qquad 4.1$$

where:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \qquad 4.2$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \qquad 4.3$$

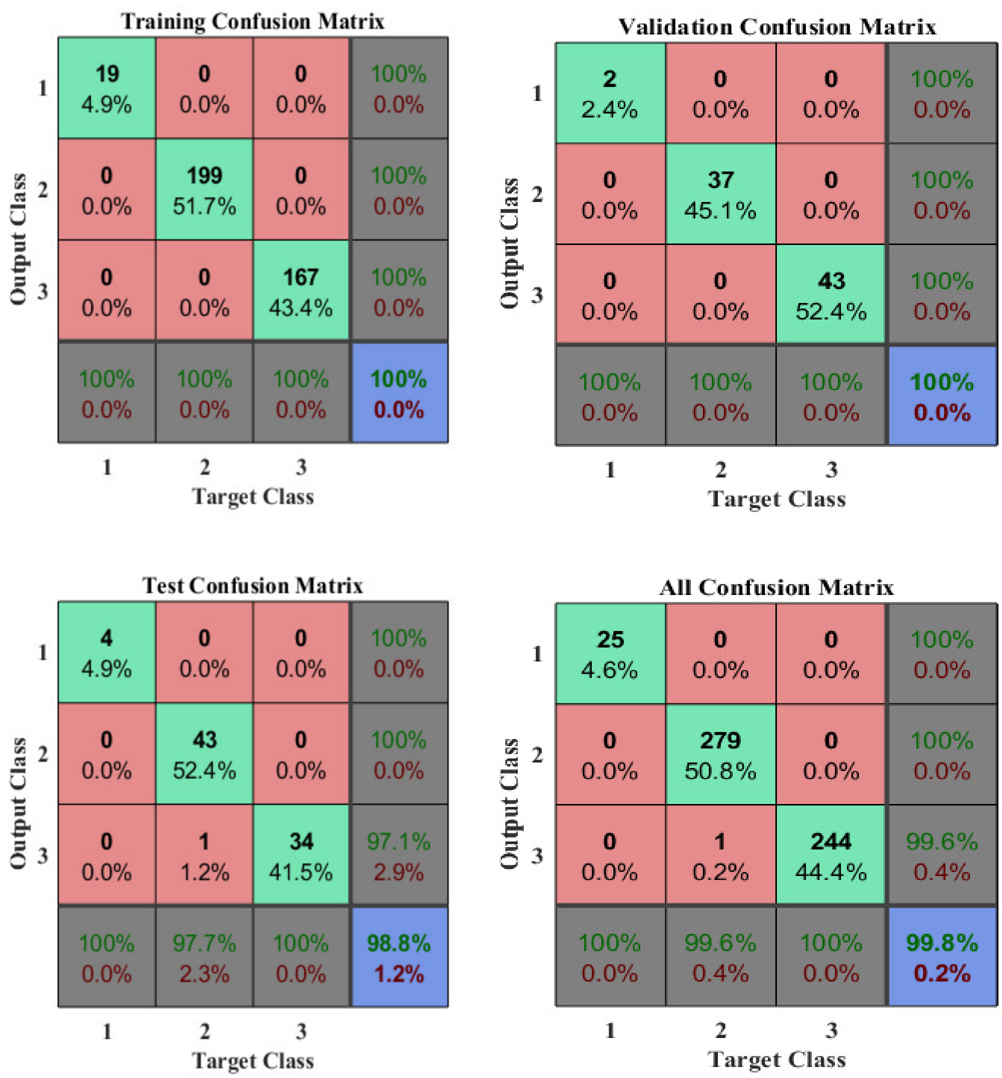


Fig. 5.5: Confusion matrix under grid-connected operation

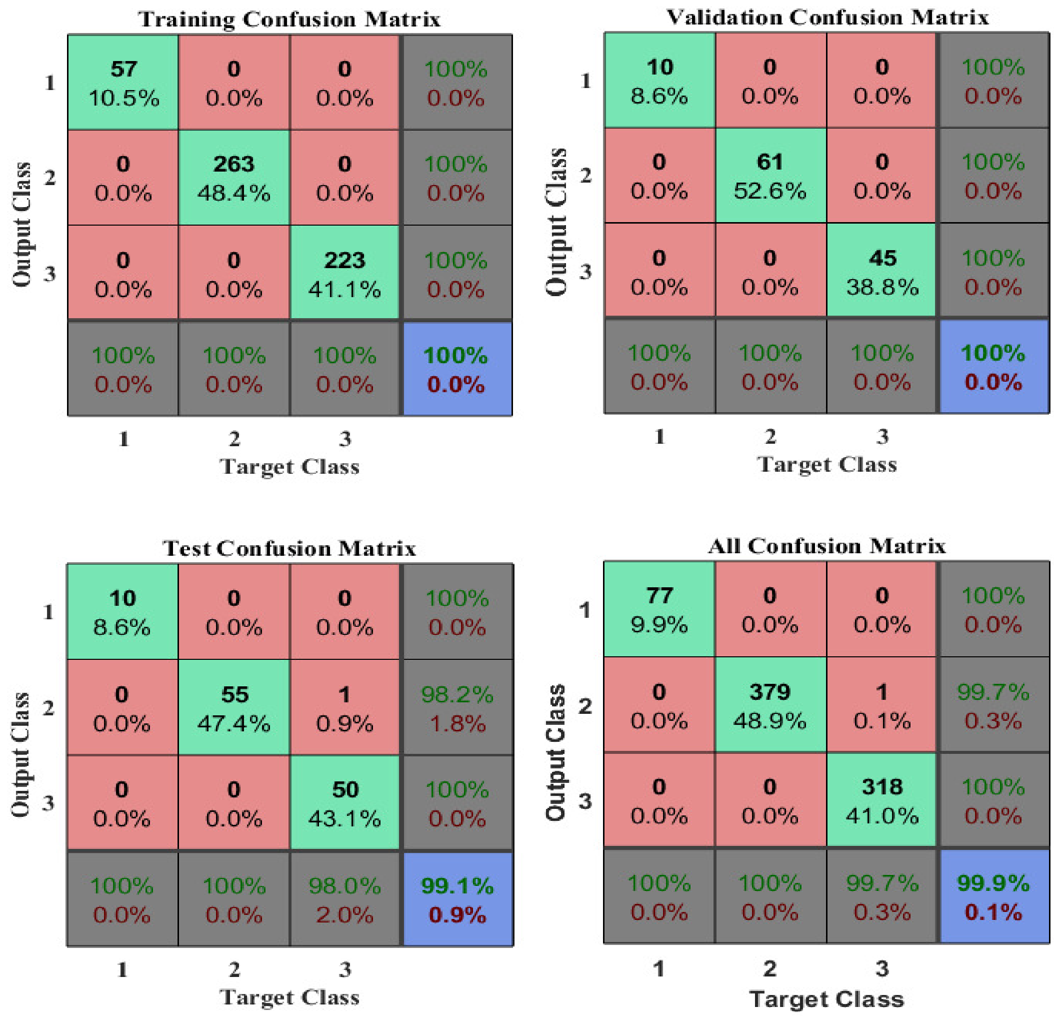


Fig. 5.6: Confusion matrix under islanded operating mode

Table IV:Statistical analysis of the suggested protection scheme's performance for the test data

Operating mode	Event	Precision	Overall accuracy	F1-score
Grid –connected mode	Normal operation	100%	98.8%	0.98
	PG fault	100%		
	PP fault	97.1%		
Islanded mode	Normal operation	100%	99.1%	0.99
	PG fault	98.2%		
	PP fault	100%		

The F1 score is found to be 0.98 and 0.99 in grid-connected and off-grid modes respectively, indicating that the suggested protection strategy is accurate and sensitive. Table IV shows the statistical metrics of ANN performance generated from the confusion matrix for test cases. The overall classification accuracy of 98.8% and 99.1% for grid-parallel and off-grid modes respectively shows that the suggested protection method offers very high fault detection and identification accuracy for DC microgrids under widely varying operating conditions.

Thus, the suggested wavelet-based technique is efficient as it is able to discriminate between normal microgrid functioning and a fault. The results show that this protection technique may be used to identify faults during both isolated and grid-parallel modes with high accuracy. As a result, this system may overcome the drawbacks of standard protection schemes in dynamic conditions, providing intelligent fault detection and identification under a variety of operating and loading conditions.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1. CONCLUSION

DC microgrids present a viable power system solution for increasing renewable energy integration while delivering evident advantages like high efficiency and simple control. Despite these benefits, the design and implementation of a potential DC microgrid protection system remain a substantial issue. In this dissertation, new fault detection and identification strategy employing wavelet transform and pattern recognition is suggested for DC microgrids.

The proposed approach uses discrete wavelet transform to extract detailed wavelet coefficients from pole and ground current signals under various fault and non-fault cases. The maximum values from the detailed coefficients are gathered and utilized to train an artificial neural network (ANN) for defect identification and classification. Using MATLAB/SIMULINK, the simulations have been performed on the DCMG model in both grid-parallel and grid-isolated modes.

Performance evaluation of the suggested protection technique revealed that it can offer precise and reliable fault detection/identification with an overall accuracy of about 98.8% and 99.1% for grid-parallel and grid-isolated operating modes respectively. The majority of available fault detection and identification approaches employing signal processing and data-driven methodologies rely on communication among devices which poses a number of implementation challenges. This technique does not use multi-terminal measurement or inter-zone communication. In addition, changes in parameters such as fault resistance, fault location, and microgrid loading level do not affect its accuracy. Furthermore, as a result, of reduced input data and the computational efficiency of wavelet transforms and ANNs, the proposed protection technique has a comparatively low computational burden. Consequently, this technique provides a reliable solution for DC microgrid fault detection and identification.

5.2. FUTURE SCOPE

The work presented in this dissertation demonstrates that the suggested approach can reliably identify faults under various system modifications. As a result, the suggested fault detection and classification technique should be able to be extended to DCMGs of various sizes and architectures. The proposed method can also be expanded to incorporate DC series faults. Furthermore, DWT-based feature extraction under various fault situations demonstrated the suggested approach's potential ability to localize faults and may be further studied.

LIST OF PUBLICATIONS

[1] Asra Irfan, Prasenjit Basak, ‘‘Fault Detection and Identification for DC Microgrid with Wavelet-based Artificial Neural Networks”, communicated to IEEE Transactions on Artificial Intelligence.

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APPENDIX

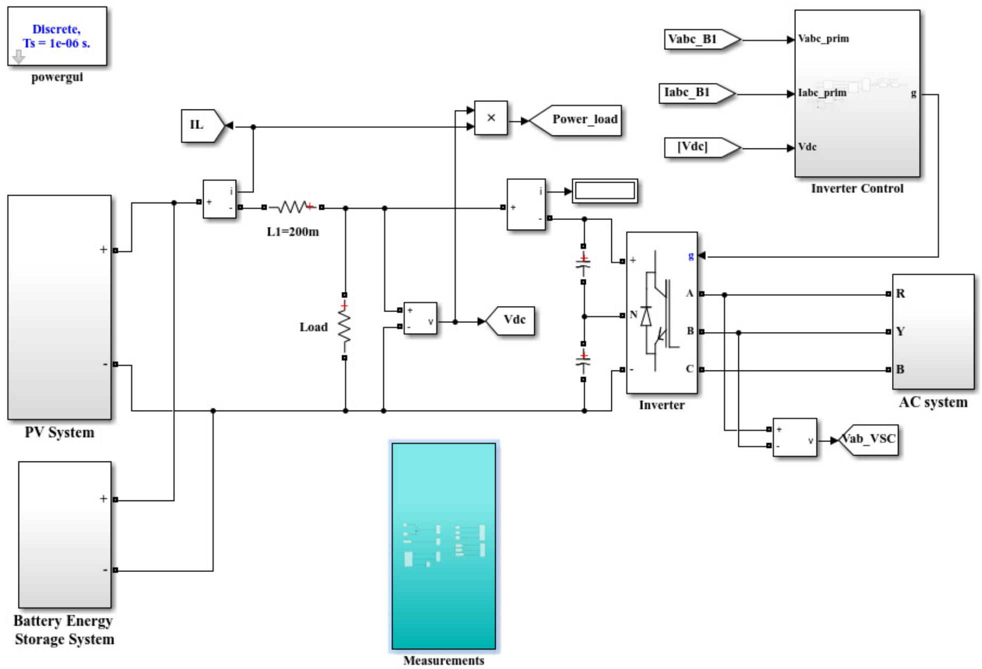

Fig. A1: Simulink diagram of the DCMG in grid-connected mode

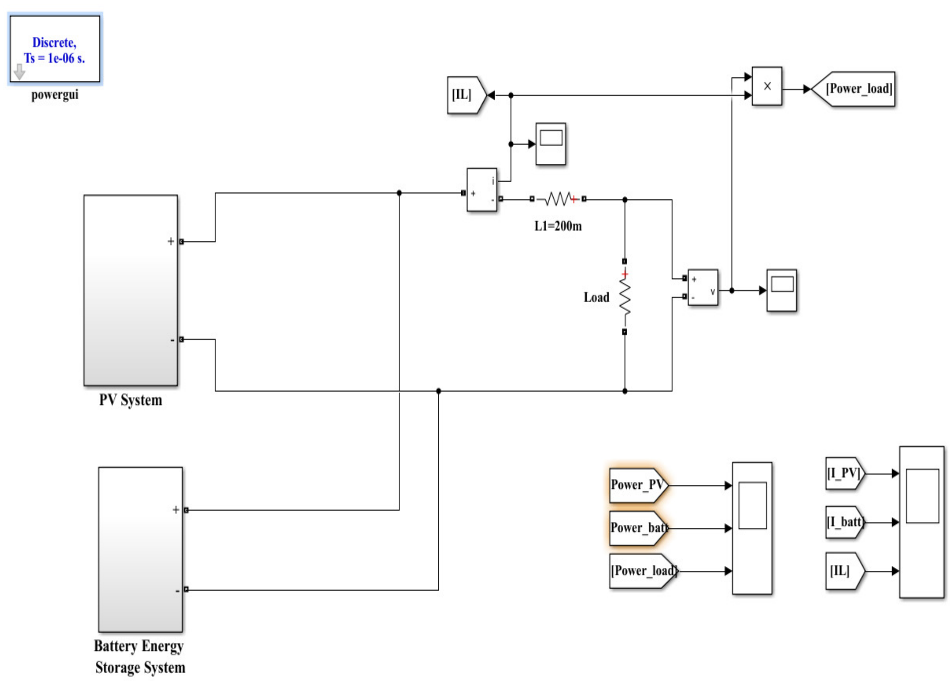

Fig. A2: Simulink diagram of the DCMG in islanded mode

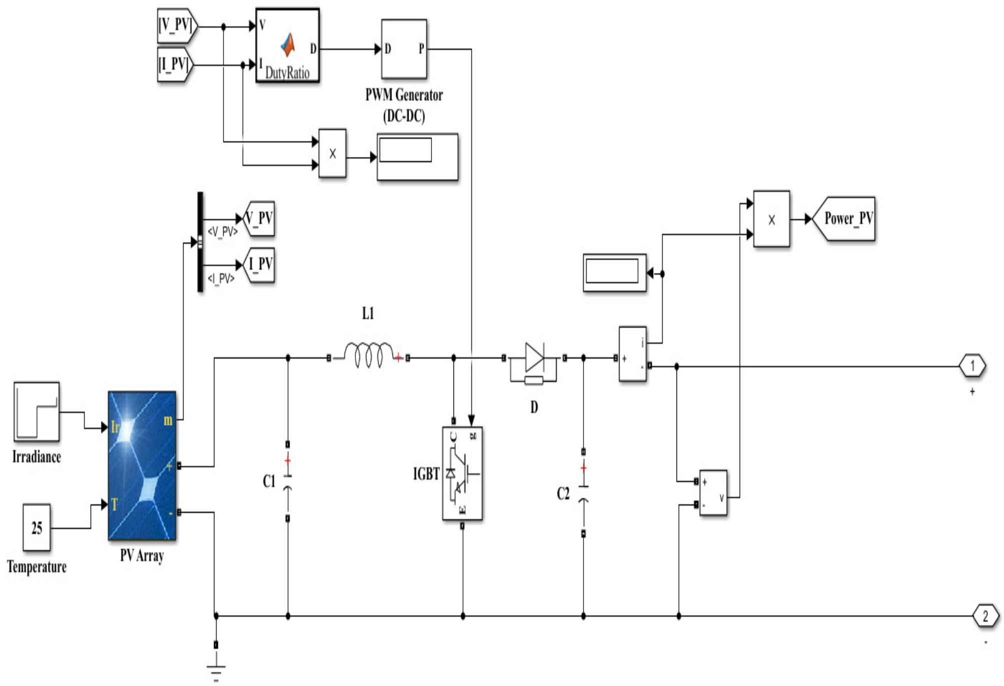

Fig. A3: Sub-system representing the PV system

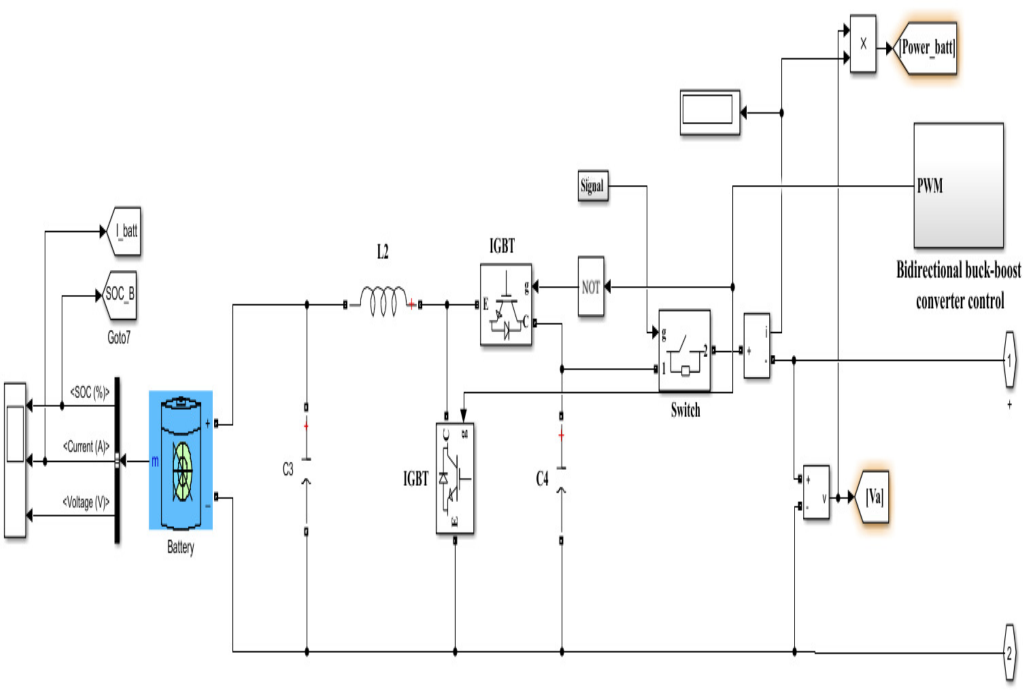

Fig. A4: Sub-system representing the BESS system

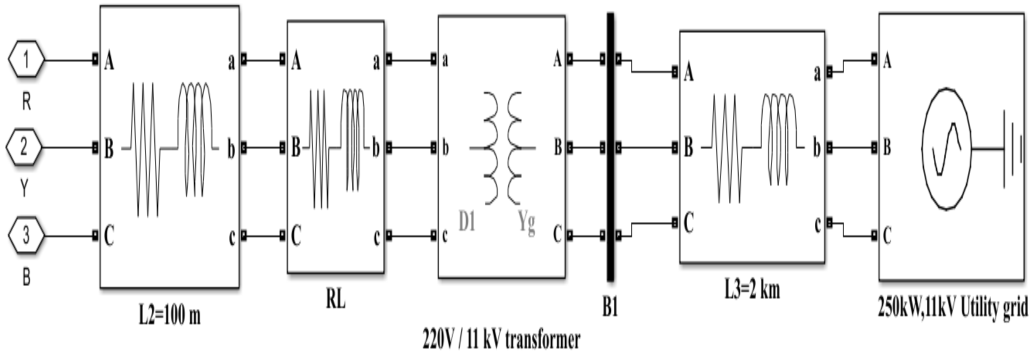

Fig. A5: Sub-system representing the AC system

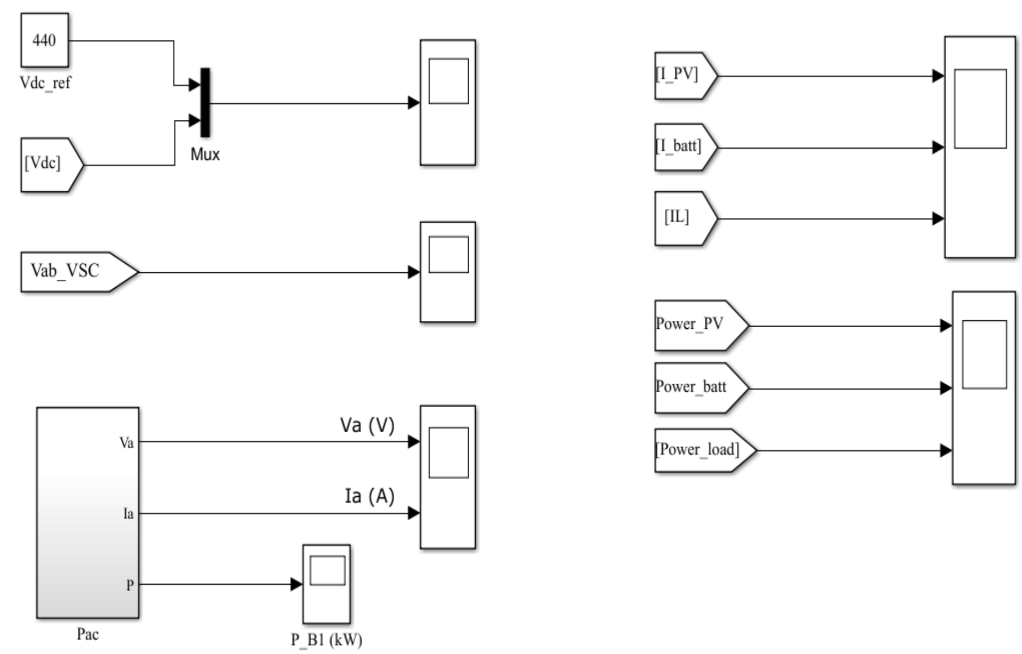

Fig. A6: Sub-system representing the measurement block

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2	Karthikeyan Subramaniam, Mahesh S. Illindala. "Intelligent Three Tie Contactor Switch Unit-Based Fault Detection and Isolation in DC Microgrids", IEEE Transactions on Industry Applications, 2020 Publication	<1%
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