Open Switch Fault Diagnosis of Cascaded H-Bridge Multi-Level Inverter Using Deep Learning

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Dedication

I dedicate this thesis to my parents, beloved siblings, teachers, and supervisor, as well as to all deserving children who lack access to quality education, with a special emphasis on young girls.

Acknowledgments

Due praises are given to Allah Almighty, the Creator, and the Sustainer, without whose instruction not a single minute pass. He who has given us forte and blessed us with plenteousness without any measure. There are no words which can do justice to Him. I am empowered to Read and Write only by Him, who has bestowed upon me the knowledge I carry forward.

I would first like to acknowledge National University of Science and Technology for providing the research facility that enabled me to conduct the research.

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I extend my sincere appreciation and deep respect to my parents for their unwavering support, heartfelt prayers, and benevolent wishes throughout my academic journey and the completion of this research. In particular, I would like to convey my heartfelt gratitude to my dear sister for her consistent encouragement and motivation at every stage of my research expedition.

Muhammad Nouman Arif

Abstract

Cascaded H-bridge 5-level inverters (CHB-5LIs) have gained significant traction in high-power applications owing to their capacity to generate fine quality output voltage with minimal harmonic distortion. However, their intricate architecture presents notable challenges for fault diagnosis, particularly concerning open switch faults. In this study, we offer a deep learning-based method for diagnosing open switch faults in CHB-5LIs. We present a simulation model of the CHB-5LI with open switch faults and generate a dataset comprising voltage waveforms for various fault scenarios. Leveraging this dataset, we train a Convolutional-1D Neural Network (CNN-1D) featuring a multi-layer architecture comprising convolutional and fully connected layers, culminating in the Softmax function for classification. Our method achieves an impressive classification accuracy exceeding 98 percent on previously unseen fault scenarios, underscoring the efficiency of our approach for CHB-5LI fault diagnosis. Additionally, we conducted a thorough analysis of CNN-1D performance and compared it with traditional and other deep learning models for fault diagnosis techniques. The accuracy of other deep learning models on the generated dataset is as follows: RNN is 88.9 percent, 1D-ResNet is 88.8 percent, and Time Inception model is 89.4 percent. Simulation results showcase that our proposed CNN-1D based approach surpasses other methods in terms of accuracy and robustness, elucidating the potential of deep learning for fault diagnosis in intricate power electronics systems. The fault diagnosis time for the proposed method as a fault finding tool for the simulation case is 0.060 ms, compared to 0.062 ms for RNN and 0.065 ms for ResNet.

In conclusion, the recommended open switch fault analysis method using deep learning is an effective and efficient way to diagnose faults in cascaded H-bridge 5-level inverters. The recommended method can significantly improve system reliability and prevent catastrophic failures. Further research can explore the applicability of the projected method to identify faults in other power electronic systems.

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Abbreviations

CHB-MLI cascaded H-bridge multiLevel inverter

CNNs convolutional neural network

DS double switch

DWT discrete wavelet transform

GD gradient descent

HHT hilbert-huang transform

KNN K-nearest neighbour

MLIs multilevel inverters

MLFF multi-layer feed forward

MRA multi-resolution analysis

NAG nesterov accelerated gradient

OSFD open switch fault diagnosis

OCF open circuit fault

PWM pulse width modulation

ReLU rectified linear unit

RPCA relative principal component analysis

SGD stochastic gradient descent

SVM support vector machine

CHAPTER 1

Introduction

In the modern era, the global transition towards sustainable energy sources has underscored the importance of advanced power electronics technologies. Among these technologies, single-phase cascaded H-bridge multiLevel inverter (CHB-MLI) has emerged as a versatile solution for numerous applications ranging from renewable energy integration to high-power motor drives. Advantages of the CHB-MLI over the conventional two-level inverters include good power quality, low harmonic distortion, and high efficiency; hence, it is very attractive in a wide spectrum of applications, both industrial and residential.

However well-favoured the features, the CHB-MLI is not free from faults and failures that may compromise the performance and reliability. These faults may arise due to component degradation, environmental factors, or operational stresses. They are quite challenging and call for safety and continuity of power electronic systems in operation. It is very important to have a timely fault detection and diagnosis process that prevents downtime of the system, keeping the cost of repair at a minimum while maintaining the safety of operation.

Fault detection in power electronic systems based on heuristic rules, mathematical models, or signal processing techniques usually appeared to be reasonable. However, what was most often lacking was their adaptability to diverse fault scenarios, which may require extensive domain knowledge for their implementation. The increasing system complexity in advanced designs of power electronic systems further hinders the process of fault detection through conventional approaches.

During the last years, deep learning methods, and in particular Convolutional Neural Networks, have boosted several fields by allowing automatic feature extraction and pattern recognition directly from raw data. In charges like image classification, speech recognition, or natural language processing, CNNs have shown surprising success due to their ability to learn hierarchical descriptions of data. This will be a breakthrough opportunity to get rid of the limitations of conventional systems and enhance the overall reliability and efficiency of fault identification by using the capabilities of CNNs in fault detection in power electronic systems.

TThis thesis focuses on the application of CNNs for fault detection in Single Phase CHB-5LI systems, which consist of many H-Bridge cells connected in a cascade pattern. The CHB-5LI topology enables the generation of multiple voltage levels by independently controlling the switching states of each H-Bridge cell. We employ a convolutional neural network (CNNs) to diagnose the faulty switch in the inverter based on the measured voltage signals. The dataset used to train and evaluate the proposed method includes different fault scenarios, including no fault, single faulty switch, and maximum 2 faulty switches at a time. The significance and contributions of this thesis are that the planned procedure can significantly better system reliability and prevent catastrophic failures. While this configuration offers advantages such as high flexibility and scalability, it also introduces complexities in fault detection due to the presence of multiple components and switching patterns.

The basic purpose of this thesis is to made a robust fault detection system capable of accurately identifying and classifying various types of faults in CHB-5LI systems. To achieve this goal, we propose a novel CNN-based approach that leverages simulated data. Specifically, we will generate simulated data from diverse fault scenarios, including open-circuit faults to train the CNN model. Subsequently, we will validate the trained model using simulated data collected for a different modulation index, ensuring its effectiveness under different operating conditions.

The structure of this thesis is design in this pattern: In chapter 2 we will provides the complete overview of the literature on fault detection in power electronic systems, highlighting existing methods and techniques. In Chapter 3, we present the theoretical background of CHB-5LI systems, including their topology, operating principles, and fault characteristics. In Chapter 4, we present the analysis of OCF types in CHB-5LI systems. Chapter 5 details the neural network working, different parameters used in deep learning model training. Chapter 6 details the proposed CNN-based fault detection methodology, covering aspects such as data preprocessing, network architecture, and training procedure. In Chapter 7, we present the results obtained from applying the proposed method to data. Finally, Chapter 8 summarizes the key findings of this research and talk about potential possibilities for future research and development.

In summary, this thesis aims to contribute to the advancement of fault detection in power electronic systems by introducing a novel CNN-based approach tailored specifically for Single Phase CHB-5LI systems. By harnessing the power of deep learning, we seek to enhance the reliability, efficiency, and safety of CHB-5LI systems, paving the way for their widespread adoption across various industrial and residential applications.

1.1 Background and scope

Power electronic frameworks are generally utilized in different applications because of their high productivity and low harmonic distortion. The evolution of power electronics technology has been instrumental in shaping modern energy systems, particularly in the context of renewable energy integration and electric power distribution. Multilevel inverters—like the Single Phase Cascaded H-Bridge (CHB) Multilevel Inverter (MLI)—have attracted a lot of interest because of its capacity to raise system efficiency, lower harmonic distortion, and improve power quality. The CHB MLI topology, consisting of multiple H-Bridge cells connected in cascade, offers versatility and scalability, making it an attractive choice for various applications.

However, the increased complexity of CHB-MLI systems also introduces challenges, particularly in fault finding and identification. Faults in power electronic systems can arise from different sources, including component degradation, manufacturing defects, environmental factors, and operational stresses. The concern is that some inverter faults, such as open switch faults, can lead to system failure and cause safety risks. Therefore, it becomes of utmost importance to detect and diagnose the faults accurately and timely in order to confirm the reliability, safety, and performance of the power electronic system.

Most of the traditional methods for fault detection are designed with heuristic rules, mathematical models, or signal processing techniques; thus, they tend to be complex, time-consuming, and require extensive knowledge of the parameters of the system. Although in some senses effective, these methods may lack adaptability toward many diverse scenarios of a fault nature and have a requirement for high domain knowledge to effect. Moreover, the high complexity of the power electronic systems in use today can pose a serious obstacle to detecting faults through the traditional means since doing so may be subject to unnecessary false alarms or not capture faults altogether. There is thus a need for an effective and accurate approach to open switch detection in the inverter.

In this work, an open switch fault diagnosis (OSFD) technique for cascaded H-bridge 5-level inverters has been developed using deep learning techniques. This developed method uses CNN for the diagnosis of the faulty switches in an inverter using measured voltage signals. The proposed method had been validated using datasets containing different types of fault scenarios, namely, no fault, single faulty switch, and maximum two faulty switches at a time. The proposed method is restricted to detecting open-switch faults only, and it uses voltage signals only. In this way, the method proposed in this paper will indeed bring much improvement in system reliability, preventing a lot of catastrophic failure. The method proposed has several advantages over traditional methods, of which some are real-time fault diagnosis, low computational complexity, and system-parameter independence. Furthermore, the proposed approach can be easily developed to diagnose faults in further power electronic systems.

1.2 Problem statement

Nowadays, among various power electronic systems, single-phase cascaded H-bridge 5-level inverters have become a critical challenge toward fault diagnosis of complicated nature and the potential impact of faults on system performance and reliability. The conventional methods of fault diagnosis are low in accuracy and efficiency; it is really hard to point out and classify different fault scenarios, which will cause prolonged downtime and maintenance costs as well as a compromised operation of the system.

The existing fault diagnosis techniques of the CHB-5LI system may have difficulty coping effectively with the complexity and diversity of possible fault patterns that could be caused, from single switch faults to diagonal switch faults, same-leg switch faults, and their combinations. This thus makes obligatory the development of advanced diagnostic approaches able to robustly detect and categorize faults, at the same time minimizing false alarms while maximizing diagnostic accuracy.

The research focuses on the application of deep learning methodologies to address these tasks in fault diagnosis in single-phase CHB-5LI systems. Deep learning provides a potential approach toward developing robust fault detection and classification algorithms utilizing the huge amounts of operational data generated by these systems. The study will develop a novel methodology for training convolutional neural networks architecture on labeled fault data so that it is able to diagnose different fault scenarios, including multiple faults occurring simultaneously, with high reliability and efficiency.

1.3 Research objectives

The main aim of this study is to develop an open switch fault diagnosis technique using deep learning in the Cascaded H-Bridge 5-Level Inverter. The specific objectives are as follows:

1. To develop a dataset of voltage signals corresponding to different fault scenarios, including no fault, single faulty switch, and maximum 2 faulty switches at a time.
2. To design a Convolutional Neural Network (CNN) architecture that can accurately diagnose open switch faults in real-time.
3. To train and evaluate the proposed method using the developed dataset and compare its performance with traditional fault diagnosis techniques.
4. To investigate the sensitivity and robustness of the suggested method to different fault scenarios and noise levels.
5. To determine the faulty switch accurately and provide recommendations for corrective measures to prevent system failures.

By completing these objectives, this study objects to contribute to improving the reliability and safety of power electronics systems, particularly in the renewable energy and electric vehicle sectors, where the cascaded H-Bridge 5-Level Inverter is broadly used.

1.4 Research contribution

This thesis contributes by utilizing deep learning technique CNNs to enhance fault diagnosis capabilities in single-phase cascaded H-bridge 5-level inverters.

- Utilizes CNNs in fault diagnosis for single-phase cascaded H-bridge 5-level inverters. Deep learning models accurately identify and classify various fault scenarios. Improved reliability and reduced downtime through accurate fault detection. Also, surpasses previous methodologies in fault detection capability.
- Demonstrates the ability to detect and diagnose faults, including up to two faulty switches simultaneously. Systematically categorizes different fault cases, providing valuable insights for maintenance. Categories include single switch faults, diagonal switch faults,

same leg switch faults, upper switch faults, lower switch faults, and scenarios with no faulty switches.

- Integrates deep learning algorithms for enhanced fault diagnosis. Pioneers a novel approach in leveraging artificial intelligence for inverter performance enhancement.
- Deep learning models offer adaptability and scalability, ensuring robust fault detection in real-world conditions. Enhances system reliability, efficiency, and performance.

1.5 Relevance to national needs

The aimed open switch fault diagnosis technique using deep learning in the Cascaded H-Bridge 5-Level Inverter has significant relevance to national needs. Power electronics systems, including inverters, play a important role in the energy sector, and their reliable operation is necessary for maintaining the stability and efficiency of the national power grid. Open-switch faults in inverters may cause severe power-grid disturbance, leading to system failure and a blackout with severe economic and social consequences. Thus, the proposed method can contribute to improving the reliability and safety of the power electronics system to ensure national grid stability and reduce the risk of blackouts. On the other hand, the accuracy of the proposed method and its capability for real-time fault diagnosis will bring down drastically the power electronic system downtime and maintenance cost to enhance the effectiveness of the national energy sector. Therefore, the relevance of the proposed method for open switch fault diagnosis of a Cascaded H-Bridge 5-Level Inverter goes beyond the immediate application and has important implications for the stability, efficiency, and safety of the national energy sector.

1.6 Advantages

The suggested open switch fault diagnosis using deep learning technique in the Cascaded H Bridge 5-Level Inverter presents some advantages over traditional techniques for fault diagnosis, such as high accuracy, real-time fault diagnosis, low computational complexity, robustness, and low cost. These advantages are described in detail here:

High accuracy

From the testing of diagnosing open switch faults in the inverter, it was realized that the technique proposed using convolutional neural networks really achieved high accuracy. The technique outperformed the traditional techniques for fault diagnosis.

Real-time diagnosis

The proposed method can detect the faults at the very moment. Therefore, the results for real-time detection and technique are of prime importance to the reliability of the inverter and to avoid catastrophic failure.

Low computational complexity

The method developed here has low computational complexity and does not demand much prior information about the parameters of the system, making it very suitable for practical implementation.

Robustness

The developed model is trained and evaluated using a dataset that includes different kinds of fault scenarios, which run from no fault to a single faulty switch and even a maximum of 2 faulty switches at once. This has guaranteed robustness and generalization of the technique developed. Therefore, it will surely support the national energy sector in achieving cost-effectiveness effectively by immensely reducing downtime and the maintenance costs of power electronic systems.

Cost-effectiveness

In the same vein, application of the recommended method would reduce greatly the downtime and maintenance costs of the power electronics systems, thus adding to the overall efficiency of the national energy sector.

Improved safety

Accurate diagnoses of the open switch faults and their location can greatly enhance the reliability and safety of power electronics systems, especially in the fields of renewable energies and electric vehicles.

In general, the proposed approach has several advantages over conventional techniques in fault diagnosis and can be well worth refining the reliability, safety, and efficiency of power electronics systems—therefore, representing a vital tool for the country's energy scenario.

1.7 Area of application

The proposed deep learning-based open switch fault diagnosis scheme for the Cascaded H-Bridge 5-Level Inverter applies to a wide array of applications in the power electronics industry. This is also true for the renewable energy sector, where inverters serve the vital purpose of converting direct current power sourced from solar panels or wind turbines into alternating current power for grid connection. The proposed method provides an accurate diagnosis of open switch faults that occur in the inverter, which can further enhance the reliability and safety of renewable energy systems. This guarantees seamless operation and reduced downtime, contributing to the improvement of efficiency and sustainability in renewable energy generation.

The proposed technique, however, could also be applied within the electric vehicle industry to drive the motor speed and torque using the inverter. Correct diagnoses of the open-switch fault in the inverter could avoid catastrophic failure and thus ensure the safety of vehicle occupants.

Other applications of the proposed method include UPS systems: in these, the inverter could be used to convert direct current power from batteries into alternating current. Proper and accurate diagnosis of inverter open switch faults might avert system failure, which could adversely affect continuous power supply to critical loads.

In general, the proposed method can be applied in a wide range of applications in the power electronics industry and could contribute to improvements in reliability, safety, and efficiency in systems involving power electronics.

CHAPTER 2

Fundamentals & Literature Review

Inverters are the most vital components of power electronics, as they convert DC power to AC power for a wide variety of applications. This chapter will present fundamentals as well as recent developments associated with inverters, particularly in the application of single-phase cascaded H-bridge inverters but more so for the CHB-5LI configuration. The chapter also provides an overview of available literature on research and developments in the area of fault detection for single-phase CHB-5LIs. It begins with the introduction of traditional fault-detection methods that rely on rule-based techniques and algorithms of signal processing, highlighting their strengths and limitations. Subsequently, the study delves into the novel trend of deep learning approaches, CNNs and RNNs, for fault detection in power electronic systems, especially single-phase CHB-5LIs. This would ensure the vision in the development of more effective and robust methodologies for fault detection of single-phase CHB-5LIs through the identification of gaps, challenges, and opportunities to be used in future research.

2.1 Inverters

An inverter serves as a power electronics apparatus employed for transforming stable Direct Current (DC) into regulated Alternating Current (AC). Controlled AC refers to the ability to manipulate two parameters of the AC signal: frequency and amplitude. An inverter is a static device capable of transforming one form of electrical energy into another but lacks the capacity to generate electrical power autonomously. It functions by receiving DC power from batteries and translating it into AC power during power outages or when required.

In the function of an inverter, a range of power semiconductor switching devices like IG-

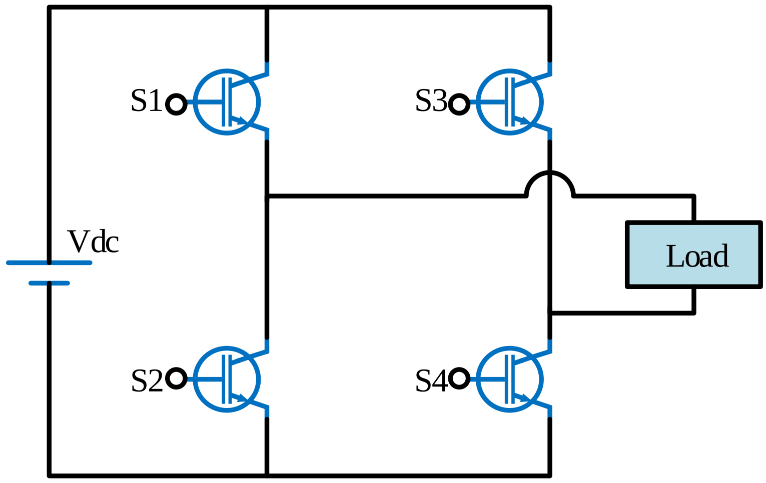


Figure 2.1: Basic three-level inverter circuit diagram

BTs, MOSFETs, and Gate Turn-Off Thyristors (GTOs) are utilized for their inherent self-commutation characteristic.

In practical applications, a power inverter plays a crucial role in translating bulk DC power into AC power, facilitating its integration into power system networks. For instance, power inverters are commonly employed at the receiving end of High Voltage Direct Current (HVDC) transmission lines, where they aid in the conversion of DC back into AC for distribution within the grid. Power inverters serve as vital components in electrical systems, enabling the efficient conversion and utilization of electrical energy across various applications, from backup power systems to large-scale power transmission networks.

Working principle of inverter

The main purpose of an inverter is to alter Direct Current (DC) power into Alternating Current (AC) power, ensuring regulation of the output signal's voltage, current, and frequency simultaneously. Essentially, an inverter operates as an oscillator.

- Transistors serve as fundamental components within inverters, facilitating the conversion of DC power into AC power. Among transistors, MOSFETs & IGBTs are widely utilized as switches in inverters.
- The number of switches employed in an inverter depends on its type and configuration.

Generally, the more switches utilized, the greater the control and efficiency of the inverter. Various types of inverters, such as single-phase inverters, three-phase inverters, and multilevel inverters, require different numbers of switches to achieve their desired functionality.

- Transistors play a important role in the transformation process within an inverter. They are responsible for converting the steady voltage and unidirectional current flow of DC into the fluctuating voltage and oscillating current of AC. The key feature of transistors in generating AC power lies in their ability to rapidly switch on or off, thereby modulating the output waveform according to the desired voltage, frequency, and current requirements.

Transistors serve as essential components in inverters, enabling the conversion of DC power into AC power through rapid switching actions, while also regulating key parameters such as voltage, current, and frequency to converge the particular needs of numerous applications.

Applications of inverter

- When the AC main power supply is unavailable, an uninterruptible power supply (UPS) relies on batteries and an inverter to provide continuous power to connected devices or systems. This setup ensures that critical operations remain functional even during power outages.

- Power inverters have various applications beyond just UPS usage. They are frequently utilized in High Voltage Direct Current (HVDC) transmission lines to change DC power into AC power at the receiving terminal. Additionally, power inverters are utilized to connect two asynchronous AC systems, synchronizing their operation, and enabling efficient power transfer between them.

- Solar panels generate DC power from sunlight. To integrate solar energy into conventional AC power systems, solar inverters are employed. These inverters translate the direct current (DC) electricity generated by solar panels into alternating current (AC) electricity, aligning it with typical electrical grids and enabling its use for residential, commercial, or industrial purposes.

In essence, while UPS systems rely on inverters to provide backup power during outages, power inverters play broader roles in electricity transmission and renewable energy integration, including HVDC transmission, synchronization of AC systems, and conversion of solar energy into usable AC power.

2.2 Types of inverters

Inverters are classified into various types based on several factors such as input voltage, output voltage, application, and power rating. Each type of inverter is designed to suit specific requirements and applications. Here are some common classifications of inverters:

Input base classification

1) Voltage fed inverter

In voltage-fed inverters, the input voltage remains constant regardless of the load demand, while the current varies based on the load requirements. This is accomplished by integrating a voltage link, often in the shape of a capacitor, between the DC power source and the inverter.

For a voltage-fed inverter, the behavior of the output is analogous to a buck converter. The output voltage from a buck converter is less than the input voltage, and this characteristic follows in the voltage-fed inverter too. It is so because, due to component losses, voltage losses, and the general design of the circuit, the root mean square voltage output is always less than the DC voltage inputted.

This inverter configuration is more commonly used in applications where a constant input voltage is required or in some industrial environments and motor drives. The capacitor embedded in the voltage link will assist to make the input voltage stable and provide a buffer against any fluctuations in the DC power source.

In simple terms, voltage-fed inverters provide a constant output voltage and yet they allow the current to change depending on load demand. They are most suitable for applications in which the input voltage has to be maintained as constant as possible, for which the properties of a buck converter are a great way to achieve these objectives.

2) Current fed inverters

This inverter operates on a special characteristic whereby the input current remains constant regardless of the load connected to it. The applied load varies the voltage to the inverter. Such an inverter uses the current link, often in the form of an inductor, between the DC power source and the inverter.

In this regard, the current-fed inverter maintains a constant input current that generally stabilizes the system independently of load variations. There is a realization of a steady input current because of the existence of a current link that aids in the regulation of current flow into the inverter.

In a voltage-fed inverter, the output voltage is constant, but in current-fed inverters, the output voltage varies with the load applied. The output voltage changes according to the demand in the load, while the input current remains constant.

The implementation of an inductor as a current link in a current-fed inverter makes it possible to control and regulate the input current, such that it remains constant under load variations. This feature makes current-fed inverters best suited to applications where the load is to be driven with a consistent input current, particularly on some types of motor drives or high-powered industrial equipment.

In general, the current-fed inverter provides input current stability, and the provision is made in such a way that output voltage changes according to the requirements. The designs with a current link that is realized in the form of an inductor help in efficient and reliable operation in such applications where constant input current is needed.

3) Variable DC-link inverters

Variable DC-link inverters belong to that variety of inverter in which the magnitude of the input voltage can be changed by changing the values of parameters of the inductor and capacitor used for the DC link. This particular configuration includes both a DC current link and a DC voltage link, interconnecting the source of DC power to the inverter, so there is maximum flexibility in changing the output voltage as required.

A variable DC-link inverter supplies the current and voltage characteristics through the inductor and the capacitor, respectively. The input values to the inverter are now manipulated to get the output voltage by controlling the component values of the inverter circuit.

The DC current link is applied in controlling the input current in such a way that the whole system becomes stable and consistent. At the same time, the input voltage can be controlled with the DC voltage link, creating flexibility in changing the output voltage to particular needs. The versatile output voltage of this type of inverter enables a wide variety of applications that need fine regulation of voltage. The inductor and capacitor parameters in the DC link can be varied to fine-tune the output voltage for various loads and operational scenarios.

Variable DC-link inverters find application in diverse fields such as motor drives, renewable energy systems, and grid-tied inverters, where the ability to adjust the output voltage enhances system performance, efficiency, and reliability.

Output base classification

1) Square wave inverter

The square wave inverter efficiently translate DC input into square wave AC output, though its high harmonic content limits its suitability for use in AC motors and transformers. Nonetheless, its development has paved the way for the emergence of more advanced and improved technologies in the field of power conversion.

2) Quasi square wave inverter

Quasi square wave inverters, a modification of square wave inverters, produce an output similar to square waves but feature zero-voltage periods before switching polarity. They offer simplicity, cost-effectiveness, and compatibility with various electronic devices, making them widely utilized despite their slightly altered waveform.

3) Sine wave inverter

Sine wave inverters produce nearly flawless sine wave outputs with a total harmonic distortion of less than 3%, guaranteeing compatibility with utility-supplied grid power and all AC electronic devices. Commonly employed in grid-tie inverters, their complex design and higher cost per unit power reflect the stringent demands of this application.

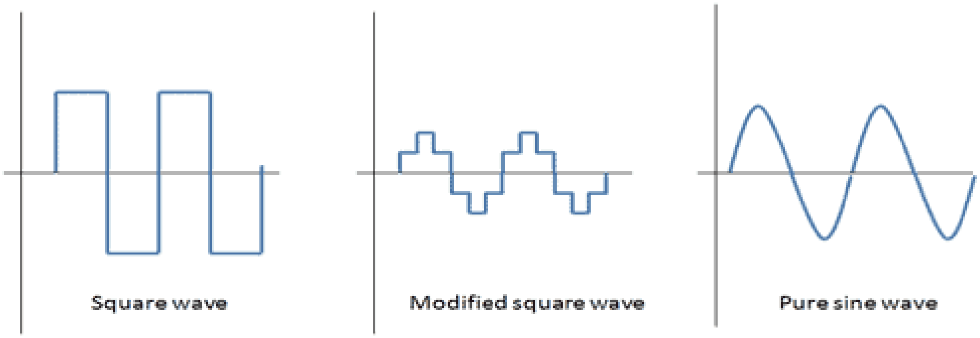


Figure 2.2: Output base classification inverter waveform

4) Multilevel inverter

Multilevel inverters are highly complex power electronic devices in which desired voltage waveforms are synthesized by the permutation of several levels of DC voltages. Several applications may incorporate multilevel inverters because they deliver high-quality sine wave outputs with low total harmonic distortion, contrary to classical inverters that deliver stepped or square wave outputs. These applications include, but are not limited to, renewable energy systems, motor drives, and grid-tied inverters.

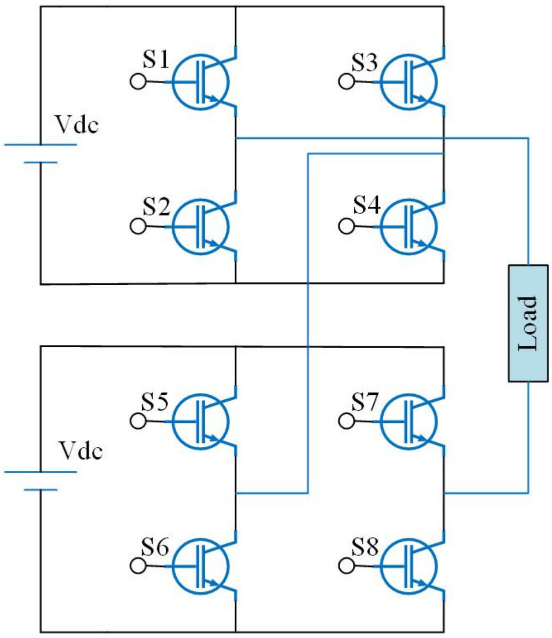


Figure 2.3: Multi-level inverter circuit diagram of CHB-5LI's

One of the greatest advantages of multilevel inverters is that they can reach a higher voltage level using power devices with a lower voltage rating. This can be done by connecting several power semiconductor devices—like IGBTs or MOSFETs—in series connections, parallel connections, or a combination of both. The connection allows the generation of several voltage levels in the output waveform.

5) Resonant inverters

This kind of inverter operates through control techniques including zero voltage switching and zero current switching, thus reducing the switching losses by ensuring that either the output voltage or current passes through zero. The circuit can hence be configured with series or parallel connection; resonant inverters can be further classified into two, series-resonant inverters, and parallel-resonant inverters.

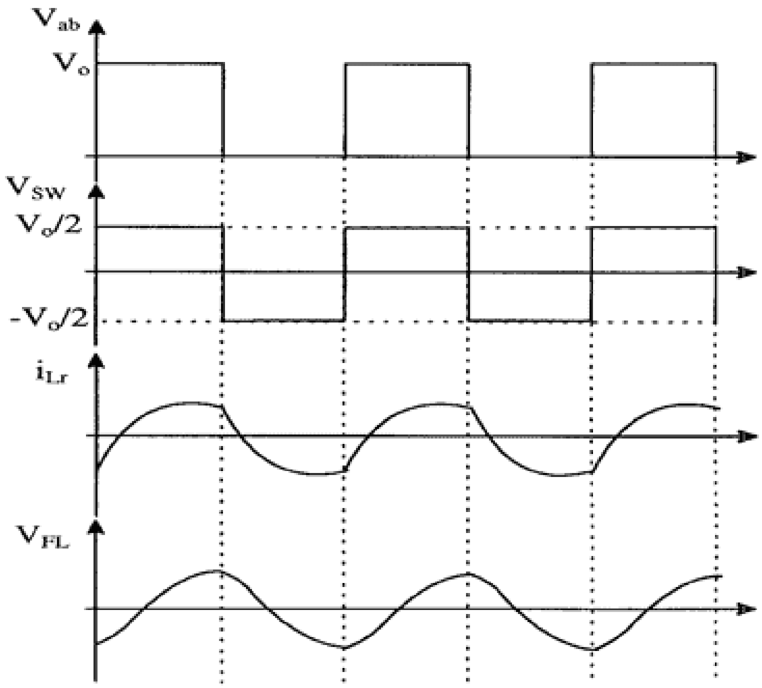


Figure 2.4: Resonant inverter waveforms

6) Boost inverter

It is one new-fashioned form of inverter that will raise the output voltage level above the input DC voltage. This is through the inclusion of a DC-DC boost converter between the DC source and the inverter, thus increasing the voltage level before it is supplied to the inverter.

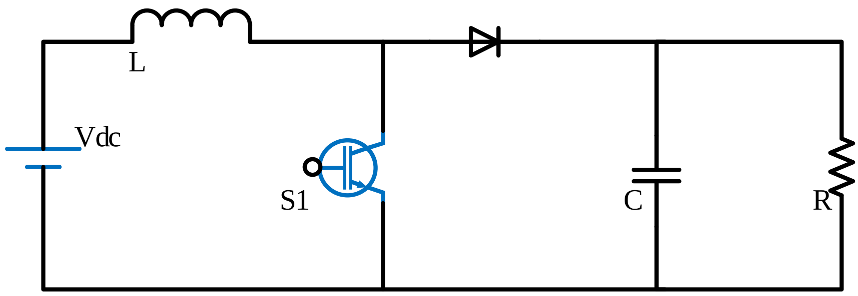


Figure 2.5: Boost converter schematic diagram

Power rating base classification

1) Single phase inverter

Single-phase inverters find common use in low- and medium-power applications or in single-phase circuit configurations because they are simple in design and cost-effective. These inverters are best applied in residential, small commercial, and light industrial settings where power requirements are relatively modest.

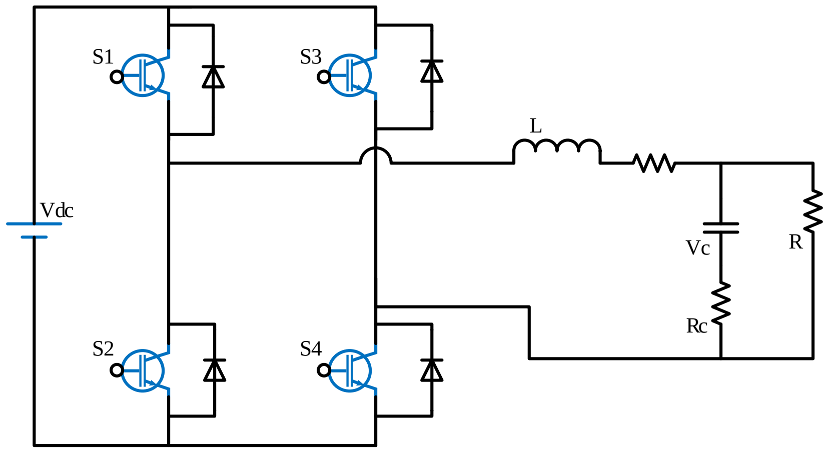


Figure 2.6: Single phase inverter circuit diagram

One of the important features available with single-phase inverters is their cost-effectiveness, which allows the inverters to be implemented in a wide variety of applications. Their simpler designs, comprising fewer elements compared to three-phase inverters, would consequently have a reduced manufacturing cost and installation cost.

Single-phase inverters are more particularly implemented in solar photovoltaic (PV) energy conversion systems; they convert the DC power generated from solar panels to AC power either for domestic or commercial use. These features make them very attractive for easy installation and usage by people who wish to utilize solar power in their homes or small businesses with an aim to reduce electricity bills and pollution caused.

However, the single-phase inverters have their disadvantages too. They are, first, limited in terms of power—they handle only so much—and not every application will suit them. In high-power industrial machinery or large commercial facilities that require three-phase power, they are unusable. Further, the single-phase systems may develop voltage imbalance conditions in the three-phase distribution network, which can further give rise to potential power quality problems.

2) Three phase inverter

Three-phase inverters are preferred in high power applications because they can handle high loads and provide balanced power in the three phases. However, the inversion in the three-phase inverters is much more complex compared to single-phase inverters, requiring more sophisticated circuitry and control algorithms.

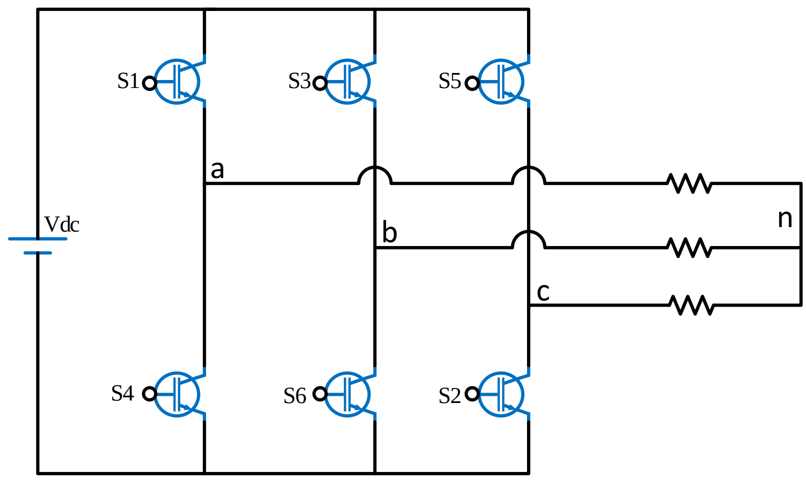


Figure 2.7: Three phase inverter circuit diagram

One big challenge that comes with three-phase inversion is obtaining a balance in the outputting of all the three phases for stable and efficient operation. In simple terms, a single-phase inverter deals with only one phase, while a three-phase inverter implies synchronizing and controlling the output of three different phases simultaneously.

For such applications, three-phase inverters are classically implemented using some power semiconductor devices, such as IGBTs or MOSFETs in topologies, which contain three-level or multi-level inverter forms. These configurations help to reduce harmonic distortion, boost power quality, and increase efficiency in applications that require high power.

Besides the complexity of hardware, three-phase inverters also need more complex control and modulation techniques. High-performance control algorithms are required to achieve superior voltage and current regulation, phase synchronization, fault detection, and protection. This calls for advanced digital signal processing techniques with real-time monitoring capabilities to enable optimal performance while ensuring reliability.

2.3 Types of faults in inverters

There are different types of faults an inverter can develop. Such types of faults may occur due to component failures, external conditions, or operational problems. Some common types of faults in inverters include:

1. **Overvoltage fault:** It is a situation where the output voltage goes above the set limit. This may occur as a consequence of sudden load variations, failure in components, or wrong settings.

2. **Undervoltage fault:** Conversely, under voltage fault is that which occurs when the output voltage goes under a specified limit. It may occur due to heavy loadings, depletion of batteries (for grid-tie inverters with battery backup), or faulty components.

3. **Overcurrent fault:** This occurs when the output current exceeds the rated limit. These overcurrent faults may occur due to a short circuit, excessive load, or power electronic components' malfunctioning.

4. **Ground fault:** Unintendedly grounding any of the output lines may sometimes be a safety hazard and can lead to inverter damage and to the equipment connected to it.

5. **Temperature fault:** Inverters are sensitive to changing temperatures, and too much heat

causes performance degradation or component failure. Temperature faults occur when the internal temperature of the inverter exceeds the safe operating range.

6. **Communication fault:** Several modern inverters are fitted with communication interfaces for monitoring and control purposes. A communication fault occurs due to data transmission or reception failures from an inverter to external monitoring systems.
7. **Software fault:** Inverters depend on embedded software for their operation. Software faults can be caused by bugs, glitches, or firmware errors, which can sometimes manifest as an abnormal behavior or malfunction.
8. **Hardware fault:** Hardware fault is a physical failure of the elements—things like power semiconductors, capacitors, transformers, or printed circuit boards. Such faults can be due to manufacturing defects, aging, or environmental stress.
9. **Insulation fault:** A fault in insulation occurs when the insulation that separates high-voltage components and low-voltage circuits or ground is ruptured. It can lead to electrical arcing or short circuit, or to electrical shocks.
10. **External faults:** Inverters may experience external faults due to lightning strikes, power surges, electromagnetic interference, moisture, dust, or corrosion.

2.4 Open circuit fault & short circuit fault

Electrical faults can be categorized into a number of faults, and among them are open circuit faults and short circuit faults. Basically, they can occur in either inverters or in general electricity circuits.

1) Open circuit fault

An open circuit fault occurs whenever the flow of electric current faces some disturbance or a break, hence breaking the flow of the current in the process. This kind of fault in an inverter may arise through the different components, such as wiring, connectors, switches, and semiconductor devices like MOSFETs or IGBTs. Symptoms of an open-circuit fault in an inverter may include lack of total output power, abnormal readings of the voltage, or failure to start or operate. Causes of open circuit faults can include physical damage, loose connections, corrosion, or manufacturing defects.

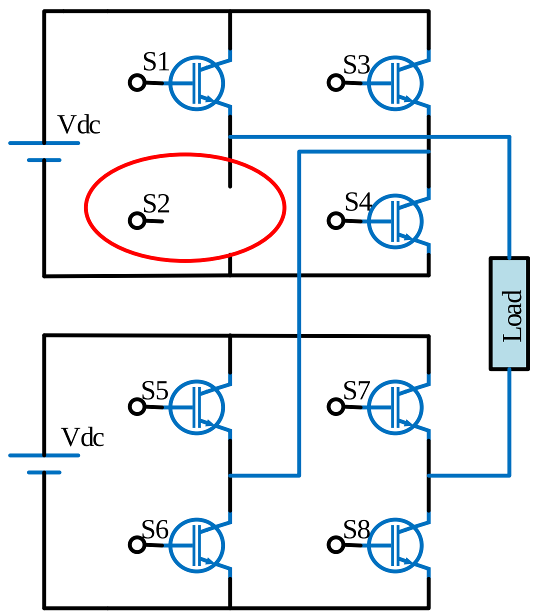


Figure 2.8: Open circuit fault in inverter

2) Short circuit fault

A short circuit fault occurs when there is an unintended connection between two points of different electrical potential, resulting in a path of very low resistance. In an inverter, a short circuit fault can happen when there's a direct connection between the positive and negative output terminals or between the output terminals and ground. Such short circuits can result in excessive current flow, which may damage components, cause overheating, or even pose fire hazards if not quickly addressed. Short circuit faults can result from insulation breakdown, damaged conductors, loose connections, or component failures. Protective devices such as fuses, circuit breakers, or current-limiting devices are often installed in inverters and electrical circuits to mitigate the effects of short circuits by interrupting the current flow and preventing damage.

2.5 Multilevel inverters

Multilevel inverters have garnered significant attention in the realm of power electronics owing to their capacity to generate intricate waveforms while exhibiting superior harmonic characteristics. Additionally, they entail diminished filter needs and alleviate voltage stress on electronic

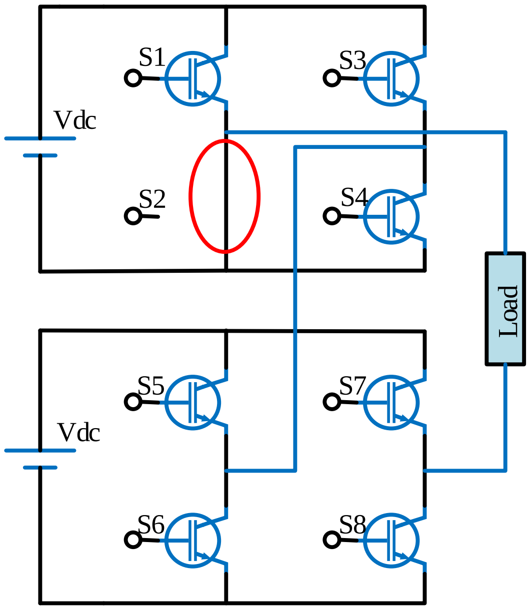


Figure 2.9: Short circuit fault in inverter

elements.

Concept and principle of operation

Multilevel inverters are a major innovation in power electronics technology, capable of producing high-quality AC waveforms with lower harmonic distortion than conventional two-level inverters. The core principle behind multilevel inverters is to create an output voltage by combining multiple levels of DC voltages, which gives them their "multilevel" designation. Unlike traditional inverters that are typically limited to two voltage levels (e.g., +V_dc and -V_dc), multilevel inverters utilize multiple voltage levels to approximate a desired output waveform, often resembling a sinusoidal voltage.

Multilevel inverter operation is based on the strategic placement and switching of power semiconductor devices, such as IGBTs or MOSFETs. These semiconductor switches are put in several-level groupings containing different voltage sources or various capacitor banks. By turning on and off these switches in a specific order, the multilevel inverter can synthesize an output voltage waveform with several discrete levels of voltage.

2.6 Types of multilevel inverters

1) Diode clamped multilevel inverter

This specific type of inverter uses diodes to distribute various voltage levels to series-connected capacitor banks. The diodes help reduce stress on other electrical components by limiting the supplied voltage. A limitation of this design is that the maximum output voltage is restricted to half of the input DC voltage. However, this can be addressed by increasing the number of capacitors, switches, and diodes. Despite this limitation, these inverters provide high efficiency and offer a simple solution for back-to-back power transfer systems.

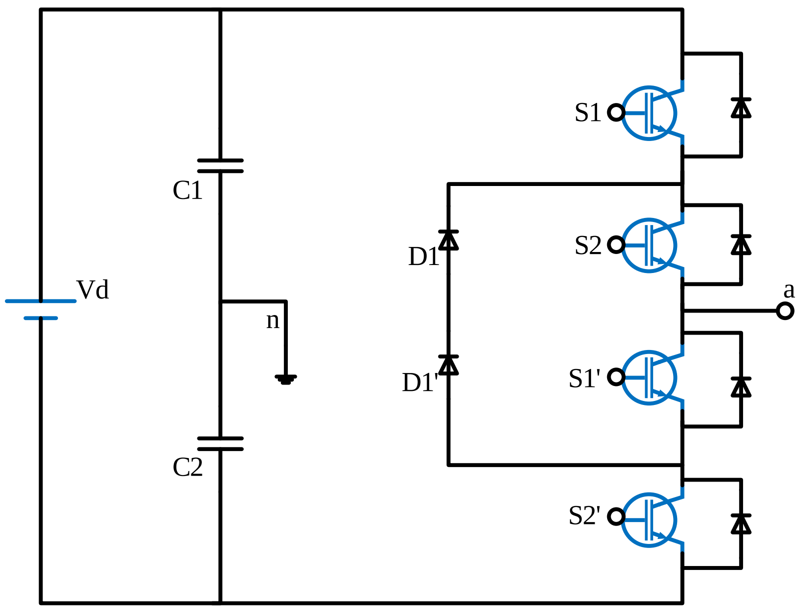


Figure 2.10: Diode clamped multilevel inverter circuit

2) Flying capacitors multilevel inverter

This topology centers around the utilization of capacitors, which facilitate the transfer of restricted voltage to electrical devices. Similar to the diode-clamped inverter, this inverter's switching states resemble those of the diode-clamped topology, eliminating the need for clamping diodes. However, it's important to note that the maximum attainable output voltage cannot surpass half of the input voltage (DC voltage). Despite this limitation, it possesses the capability to regulate both active and reactive power flow. Nevertheless, the high-frequency switching characteristic of this topology may result in switching losses.

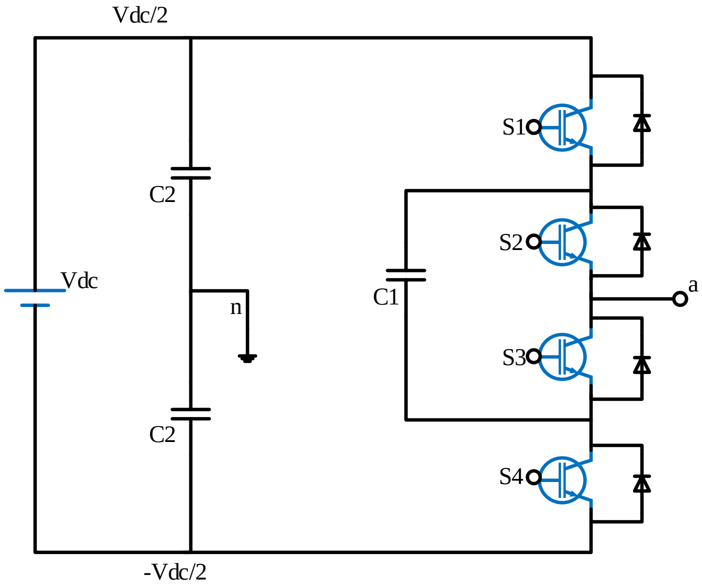


Figure 2.11: Diode clamped multilevel inverter circuit

3) Cascaded H-bridge multilevel inverter

The CHB-MLI's is an advanced topology in power electronics, especially suited for high-voltage and high-power conversion applications. It consists of various H-bridge modules connected in series, which is why it's called "cascaded." Each H-bridge module contains several power semiconductor switches, usually IGBTs or MOSFETs, as well as capacitors.

The operational foundation of the CHB-MLI's relies on synthesizing output voltage levels through selective switching of the H-bridge modules. By managing the switching states of each H-bridge module, the inverter can produce various voltage levels at its output terminals. This capability enables the approximation of a desired sinusoidal waveform with minimized harmonic distortion. An advantage of the CHB-MLI's is its scalability. The quantity of H-bridge modules can be adjusted to match the precise voltage and power needs of the application. Additionally, this topology offers improved voltage balancing across the capacitor voltage levels, enhancing the whole efficiency and reliability of the inverter.

In general, the cascaded H-bridge multilevel inverter finds wide applicability in different fields such as renewable energy systems, motor drives, grid-connected power converters, and high-voltage direct current (HVDC) transmission systems. The reasons for such an acceptability

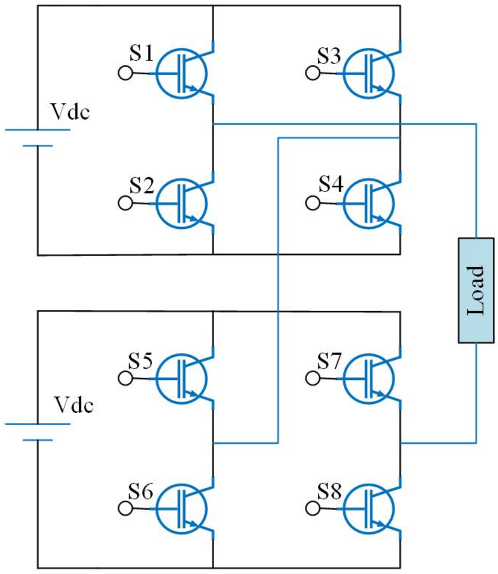


Figure 2.12: Cascaded H-bridge five level inverter circuit

in recent power electronics are its capability to produce better output waveforms with least harmonic distortion, scalability, and dependability.

2.7 Open switch fault in CHB-5LI's

An open switch fault is a type of fault that occurs in power electronic systems, such as the CHB-5LI's, when one or more switches in the inverter fail to operate or open circuit. This fault can result in a huge increase in voltage and current stress on the remaining switches, causing system failures that are dangerous to safety. Therefore, it is critical to detect open switch faults within the inverter and take appropriate corrective measures to prevent catastrophic failures. Varied methodologies can be employed for diagnosing open switch faults, ranging from traditional methods that are based on voltage and current measurements to more sophisticated approaches based on deep learning methodologies.

The CHB-5LI is a type of multilevel inverter widely used for power electronics applications. It consists of two H-Bridge modules that are connected in series. Each H-bridge module comprises four switches that can be controlled to produce output at various voltage levels.

The inverter is capable of adding up the output voltages of each H-bridge module to develop several levels of output voltage, hence termed as a "5-level" inverter. The cascaded H-bridge 5-level inverter is popular primarily for its rugged power handling capability, features for low

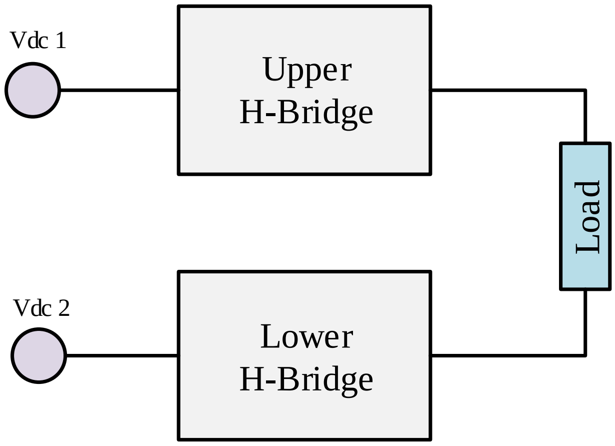


Figure 2.13: Block level circuit diagram of cascaded H-bridge inverter

harmonic distortion, and applicability to a variety of input voltages, and it is commonly used in applications like renewable energy systems, electric vehicles, and industrial automation.

2.8 Fault diagnosis in 5 level inverters

The fault diagnosis in 5 level inverters is defined with different aspects below:

Basic fault diagnosis in 5 level inverters

Fault diagnosis in five-level inverters pertains to identifying and troubleshooting issues that might arise in the inverter's circuitry or components. Inverters working with five levels require careful analysis to pinpoint problems accurately, given their increased complexity compared to simpler models. A general approach to fault diagnosis is:

1. **Visual Inspection:** Look for physical damage and loose connections in the inverter circuitry, and signs of burnout such as components burnt out or yellowing circuit boards.

2. **Check Power Supply:** Check that the power supply to the inverter is stable and that the voltage and frequency are within the specified range. Fluctuations or irregularities in the power supply can cause several problems with the operation of the inverter.

3. **Monitor Output Voltage and Current:** Measure the output voltage and current using

appropriate measuring instruments. Any deviation from the ideal value with the discrepancy among the actual measured values can indicate some fault in the inverter circuitry.

4. **Thermal Imaging:** There is thermal imaging with infrared cameras for detecting hot spots or places where too much heat is in the inverter components. Overheating may mean malfunctioning components or a lack of proper cooling method.

5. **Check Gate Signals:** Verify that the gate signals provided to the semiconductor switches (such as IGBTs or MOSFETs) are correct and synchronized. Incorrect gate signals can lead to improper switching of the power devices and result in inverter malfunction.

6. **Inspect Protection Circuits:** Ensure that the protection circuits, such as overcurrent protection, overvoltage protection, and short-circuit protection, are functioning correctly. These circuits are crucial for safeguarding the inverter and connected devices from damage under fault conditions.

Fault diagnosis in 5 level inverters using machine learning and deep learning

Fault diagnosis in 5-level inverters using machine learning and deep learning techniques involves leveraging data collected from the inverter's operation to train models that can automatically detect and classify different types of faults. Here's a general approach:

- **Data Collection:** Gather data from sensors installed in the inverter system during normal operation as well as under various fault conditions. The data should include measurements such as voltages, currents, temperatures, and switching patterns.

- **Feature Extraction:** Extract relevant features from the collected data that can help differentiate between normal operation and different fault scenarios. These features may include harmonic content, transient characteristics, frequency spectrum, and statistical parameters.

- **Labeling:** Annotate the collected data with labels indicating the presence and type of faults. This step is crucial for supervised learning, where the model learns to associate specific patterns in the data with corresponding fault classes.

- **Data Preprocessing:** Preprocess the data to handle missing values, remove noise, normalize or standardize features, and balance the distribution of samples across different fault classes. Proper preprocessing ensures that the data is suitable for training ML and DL models.

- **Model Selection:** Select suitable machine learning and deep learning models depending on the data characteristics and the intricacy of the fault detection task. Commonly employed models encompass support vector machines, decision trees, random forests, convolutional neural networks, and recurrent neural networks.

- **Training:** Train the selected models using the labeled data. During training, the models learn to map input features to the corresponding fault classes by minimizing a suitable loss function. Hyperparameter tuning may be performed to optimize the performance of the models.

- **Validation:** Assess the trained models using an independent validation dataset to gauge their performance and ability to generalize. Metrics like accuracy, precision, recall, F1-score, and confusion matrix can provide quantifiable measures of the models' performance.

- **Testing:** Test the trained models on unseen data, including data collected from the inverter system during real-time operation. This step helps validate the effectiveness of the models in detecting faults accurately and reliably.

- **Deployment:** Integrate the trained models into the inverter system for real-time fault detection and diagnosis. This may involve implementing the models on embedded systems or edge devices capable of processing sensor data in real-time.

Overview of fault diagnosis using CNN-1D

The main objective is to improve fault diagnosis accuracy for the H-bridge cascaded five-level inverter, focusing on identifying single switch faults and double switch faults within a single phase. In this approach, output voltage signals are utilized as the sampling data for fault diagnosis techniques employing the CNN-1D model.

A one-dimensional convolutional neural network (CNN-1D) is employed for fault classification. The CNN-1D architecture learns hierarchical features from the input data. It can effectively capture temporal dependencies and patterns in the voltage signals.

The proposed technique attains superior diagnostic accuracy, reduced identification errors, and enhanced efficiency when contrasted with conventional SVM and other traditional diagnostic methods. Employing CNN-1D for fault diagnosis in multilevel inverters represents a novel strategy, particularly effective in addressing open-circuit faults. The CHB-5LI's stands to gain substantially from the implementation of this advanced technique.

2.9 Literature review

Cascaded H-Bridge 5-Level Inverters (CHB-5LIs) have been generally utilized in high-power applications due to their capability to generate good-quality output voltage with low harmonic distortion. However, fault diagnosis of CHB-5LIs remains a challenging task due to the complexity of their structure and the variety of fault types that can occur. Among the different types of faults that can occur in CHB-5LIs are classified into two categories:

1. Open switch faults.
2. Short circuit faults.

Open switch faults occur when one or more switches in the inverter fail to conduct properly, leading to an interruption in the current path. Short circuit faults occur when two or more switches in the inverter conduct simultaneously, creating a direct current path between the DC source and ground. Both types of faults can result in abnormal voltage waveforms and can damage the inverter and connected devices if not detected and rectified in a timely manner. In this paper our primary focus is on open switch fault in CHB-5LI's.

Open switch faults can lead to significant damage to the inverter and the connected load and can even pose a safety hazard in some cases. Therefore, early detection and diagnosis of open switch faults is essential for ensuring the reliability and safety of CHB-5LIs in high-power applications. Traditional fault diagnosis methods for open switch faults in CHB-5LIs typically rely on mathematical models and signal processing techniques, which can be complex and time-consuming.

To overcome the aforesaid problems, the application of fault diagnosis and localization is of great interest in academic and industry. Two types of approaches used to kill this issue:

1. Hardware-based
2. Software-based

Several hardware based approaches have been suggested to detect and diagnose faults in CHB-5LI's. Traditional fault diagnosis methods rely on signal processing techniques such as wavelet analysis, Fourier analysis, and time-frequency analysis to extract features from the measured voltage or current signals and identify the type and location of faults.

The reliability of conventional multilevel topologies poses a significant concern, primarily stemming from the increased complexity due to a higher number of switches and accompanying driving circuitry. When encountering open or short-circuit faults, these multilevel systems often experience distortion in their output voltage, leading to potential malfunctions within the inverter. Such failures can propagate to more serious levels down the chain, which could impair the resiliency of the power grid and trigger other failures. Tackling these issues of reliability allows for the proper functioning of power systems, without which cascading failures can put at risk the integrity of the grid [8] and [27].

Wang et al., 2016, proposed an effective approach to fault diagnosis in CHB-5LIs based on discrete wavelet transform (DWT) for the extraction of features from voltage and current signals. The proposed method exhibits a high accuracy of over 96% in identifying faulty switches. However, this approach puts a heavy demand on computational resources required for DWT of the voltage and current signals; this may limit its real-time implementation in practical applications. However, some important conclusions regarding the use of signal processing techniques in fault diagnosis of complex power electronic systems could be drawn from the research paper.

Recently, a study by Sun et al. (2019) on fault diagnosis for CHB-5LIs, based on hilbert-huang transform (HHT), applied in the context of voltage and current signal analysis, showed that the approach has outstanding performance in practice with an accuracy rate of more than 97% in detecting faulty switches. However, the latter is susceptible to noise and artifacts in the signals and poses the highest possible sensitivity to the HHT method. Further directions in increasing applicability and reliability of the proposed approach involve further research on signal denoising techniques and robustness of the HHT method.

Although Zhang et al.'s (2017) proposed model-based method for diagnosis of faults in CHB-5LIs proved an accuracy of over 95% in identifying the faulty switches, it is subjective to the accurate and precise values of the equivalent circuit model parameters, which can prove cumbersome to obtain under practical conditions due to many uncertainties and complexities associated with the system under investigation. More studies on developing strong and adaptive models capable of handling system variations and uncertainties would be necessary to raise the practicality and reliability of the proposed approach.

For instance, Chen et al., 2018 developed a fuzzy logic-based fault diagnosis approach for CHB-5LIs using only voltage measurements and it achieved an accuracy of over 90% in identifying the faulty switches. The mentioned strategy should necessarily have the a priori information about and experience in designing the fuzzy logic system. Thus, the applicability of the approach is limited to complex power electronics systems. Nevertheless, the study points out to the high efficiency of the fuzzy logics-based methods in fault diagnosis, particularly for systems when only voltage measurements are available. The development of this fuzzy logic system should have the ability to increase practicality and adaptability in future fault diagnosis systems for CHB-5LIs. In general, the proposed method provides a promising approach for fault diagnosis in CHB-5LIs and gives important insights into the use of fuzzy logic-based techniques in power electronic systems.

Farhadi and Babaei introduced the new configuration, called the cross-switched MLI, which eliminates the use of a lot of power electronic switches [9]. One of the major advantages of this configuration is that it utilizes moderately rated voltage switches, while not calling for many polarity considerations in the design. This makes the proposed topology especially suitable for applications that require static volt-ampere reactive generation and magnetic resonance imaging. This can be underlined as one of the many advantages of using such a topology, which will definitely help in meeting some of the issues in power electronics by enhancing the efficiency and reliability greatly.

In the paper [19], the 5-level single-phase Voltage Source Inverter (VSI) was presented with two bidirectional switches. The main goal was to reduce the complexity of components in the system and minimize the number of gate drives required. The control strategy for the VSI used a space vector current controller and tried to simplify its design. This topology, however, did not do a good job in reducing the component count and voltage stress. Similarly, Masaoud et al. used the VSI and implemented a 5-level three-phase DC link inverter in three phases to reduce the numbers of sources, gate drives, switches, and installation area. Their method relied on the modulation of the VSI through its switching states. However, this topology faced challenges in meeting higher voltage level requirements, underscoring limitations despite attempts to optimize system efficiency and complexity.

In the domain of fault diagnosis for AC drives powered by voltage source inverters, two methodologies have been suggested in [1] and [2]. These approaches concentrate on detecting faults in semiconductor switches by analyzing the motor current's Park's vector patterns. These methods rely on output currents, leading to classification accuracy fluctuations with varying loads. Another research examines fault detection in a five-level diode-clamped multilevel inverter by employing wavelet analysis on the output voltages and input DC currents, as discussed in [13] and [11]. However, the use of input current introduces challenges, particularly under significant load variations, which may result in misinterpretation. In [35], a method is discussed for detecting open-circuit faults in loads and semiconductors. The authors employ discrete wavelet transform-based analysis, utilizing switching pulses and corresponding line voltages for fault classification. Detection occurs when the line voltage magnitude falls within a specified threshold, signaling a fault. Subsequently, fault classification algorithms are initiated, utilizing the multi-resolution analysis (MRA) of wavelet transform to derive distinct fault features from the measured line voltages.

In [5], a fault detection scheme based on frequency-domain analysis is introduced, offering the capability to distinguish between faults and transient events. However, implementing this method requires a specialized and complex filtering circuit. Additionally, phase angle oscillations at higher output voltage levels can reduce the efficiency of the classifier. Alternatively, [16] introduces an Open Switch Fault (OSF) detection method specifically designed for Cascaded H-Bridge Multilevel Inverters (CHB MLI). This approach uses asymmetric zero-voltage switching and is based on analyzing the slope of the fault current. This approach is specifically designed for CHB MLI systems utilizing rotating carrier pulse width modulation (PWM) and requires m cycles to detect OSF in an inverter comprising m H-bridges. Meanwhile, [20] suggests a diagnostic approach that employs instantaneous voltage error for fault detection, with classification achieved by altering switching sequences. However, this technique requires knowledge of switching states and current directions for accurate classification, as well as fault verification to pinpoint fault locations.

In [17], proposes a fault diagnosis scheme for the identification of Open Switch Faults (OSF) in IGBTs and clamping diodes of a NPC Multilevel Inverter. This method injects reactive power for switches fault classification and is, therefore, applicable to grid-connected systems. [18] presents a diagnostic strategy based on neutral point current changes, which are the only characteristics of the T-type MLI. This method is based on a look-up table and must also know the current switching state when fault classification has to be implemented.

Presented in [6], the neutral shift technique also provides a workaround to identify open-circuit faults, but it is specifically designed for phase-shifted Pulse Width Modulation (PS-PWM). Its application to Less-Shifted PWM configurations may thus be less accurate than that. So now arises the need for some method of fault detection that satisfies three really critical criteria: 1) low implementation cost so as to be practically feasible across the wide range of setups; 2) very high accuracy, since this is essential for reliable fault detection; and 3) fast response times for quick identification and mitigation of faults in maintaining system integrity.

Outlined in [7], a straightforward fault-detection and mitigation method is introduced, which involves computing the root mean square value of the output voltage. This method then utilizes the discrepancy among the expected rms voltage and the measured rms voltage to identify faults. However, due to its reliance on rms voltage measurement, this approach is noted for its relatively slower response time likened to other fault-detection methods.

The five-level inverter topology described in both [22] and [29] includes four unidirectional switches, two bidirectional switches, and two DC power supplies. According to [22], this topology operates reliably only in the presence of open-circuit faults. However, in certain scenarios, it becomes difficult to maintain the output voltage at the input voltage level during open-circuit fault conditions. On the other hand, [29] requires additional fast-acting fuses to ensure a short-circuited switch functions as an open circuit failure, since the topology cannot handle short-circuit faults. Furthermore, [29] highlights disparities in the topology's ability to handle faults among switches. While it can compensate for open-circuit faults in some switches to maintain consistent output voltage levels, it fails to adequately address faults in other switches, resulting in reduced output voltage levels post-fault.

The configuration detailed in [21] incorporates four additional switches designed to bypass faulty cells, consisting of two normally open and two normally closed switches. Notably, the switches employed in this setup are electro-mechanical, known for their slower response times compared to semiconductor devices. This reliance on electro-mechanical switches leads to elevated conduction losses, as two switches per H-bridge remain constantly activated during regular operation. Consequently, the continuous activation of these switches generates increased losses and heat within the system, potentially compromising overall efficiency and reliability.

An alternative approach entails implementing a redundant backup system, although this invariably escalates the total cost of the system. Redundancy is accomplished by bypassing and isolating a faulty cell, with compensatory measures such as employing backing systems like an additional H-bridge or batteries to fill in the missing voltage level. This method effectively ensures the stability of the inverter operation while sustaining the equal output voltage level. But, the incorporation of an additional DC source results in increased system costs and heightened control complexity, as noted in [10], [14].

From the aforementioned it can be concluded that signal processing-based fault diagnosis methods suffers from drawbacks of using mathematical models and signal processing techniques, which can be complex and time consuming. Contrary to the signal processing-based approaches, several machine learning-based methods have been offered in the existing literature to detect and diagnose faults in CHB-5LIs. The use of machine learning techniques for fault diagnosis in CHB-5LIs is a challenging task due to the complex nature of the system and the different types of faults that can occur.

Various classifier algorithms, heuristic methods, and statistical feature optimization techniques, initially created for different applications, have been adapted for detecting switch faults in the cascaded H-bridge multilevel inverter (CHB-MLI), as outlined in [23]. However, these methods generally involve greater computational complexity and require extensive training for the classifier, leading to longer detection times. Additionally, implementing these schemes in hardware often demands advanced processors. In [23], a mode for diagnosing Open Switch Faults (OSF) in CHB-MLI is suggested, utilizing a fast Fourier transform principal component rearrangement with a backpropagation neural network. However, due to its computationally intensive steps, which include complex matrix operations, this method requires nearly two fundamental periods to detect faults. Another detection approach, outlined in [24], utilizes an artificial neural network to detect faults in an asymmetric CHB-MLI using output voltage. Nonetheless, this technique is not appropriate for symmetric CHB-MLI configurations, as it faces challenges in precisely determining the location of Open Switch Faults (OSF) within a bridge for symmetrical inverters.

In [3], an open-circuit fault detection technique for a Cascaded H-Bridge (CHB) system is implemented using artificial intelligence-based methods. The detection of the faulty switch is done through monitoring the output voltage of the CHB. However, this approach mandates a substantial amount of training data time to encompass the operational range, ultimately leading to inaccurate results. Conversely, [8] presents a successful method for identifying faulty switches in a Neutral Point Clamped (NPC) configuration feeding an asynchronous motor drive. Nonetheless, this method necessitates the incorporation of additional current sensors in each of the NPC legs to achieve effective fault detection.

Machine learning algorithms have gained widespread application in the power industry, as evidenced by the work of Narciso and Martins [31], who provided a comprehensive review of their utilization for studying energy efficiency. In [30], a combination of a backpropagation neural network and a genetic algorithm is utilized for fault detection tasks. Specifically, the voltage across the bridge arm serves as the diagnostic signal for fault detection. The input data for the backpropagation neural network includes DC components in addition to fundamental and harmonic frequencies. The genetic algorithm aids in optimizing the weights and thresholds within the backpropagation neural network. While this method proves effective in detecting individual switch faults, it necessitates a considerable computational effort.

In [28], a fault detection method grounded in fuzzy logic is presented for identifying single and multiple switch faults in motor drives. This approach utilizes the phase current of the drive as a parameter for identifying faults. However, the primary drawbacks of fault detection based on fuzzy logic include the lack of a systematic approach and slower response times. Although effective in detecting faults, accurately determining the exact location of faults in diagonal pairs of switches within the CHB-MLI presents difficulties due to the identical fault characteristics. Consequently, there remains a gap in research concerning the determination of the exact locations of faulty switches in scenarios involving multiple faults.

In [25], the author presents an intelligent fault detection (FD) method targeting the identification of single switch gate drive faults on the CHB-MLI. The proposed FD technique utilizes two separate machine learning (ML) algorithms: support vector machine (SVM) and K-nearest neighbour (KNN). Among these, the PPCASVM-based ML algorithms are recognized for offering the most precise and effective fault detection. However, it's important to highlight that the methodologies described in both [25] and [32] concentrate solely on detecting single switch (SS) faults in CHB MLI and do not encompass the detection of faults in multiple switches.

In [12], a combination of the support vector machine (SVM) model and relative principal component analysis (RPCA) is employed to introduce a simple and fast diagnostic method for detecting open switch faults in cascaded H-bridge multilevel inverters. This paper mounts a classification algorithm that is comparatively less complex, enabling accurate identification of fault locations within a single cycle of the output voltage. Specifically, the analysis focuses on single switch open faults in the context of 5-level cascaded H-bridge multilevel inverters.

The existing machine learning based approaches, while showing promise in fault detection and localization, exhibit limitations that necessitate a transition to deep learning. Traditional machine learning struggles to unravel the intricate fault patterns inherent to complex systems like multilevel inverters (MLIs). The reliance on manually engineered features impedes its adaptability to the diverse fault scenarios and temporal dependencies present in MLIs. Consequently, the research pivot to deep learning, exemplified by the CNN-1D architecture, becomes crucial to overcome these constraints, enabling automatic feature extraction and enhancing the accuracy and efficiency of fault diagnosis in the realm of CHB MLIs.

2.9.1 Identification of research opportunity

The review of existing literature underscores the pressing requirement for advancing fault detection for inverters. The impetus for the proposed research can be succinctly encapsulated as follows:

- **Refining Fault Localization:** Current fault detection approaches manage to detect faults but struggle to accurately pinpoint the specific location of faults in diagonal pairs of switches within CHB MLI. The inherent similarity in fault features adds complexity to this challenge, leaving a gap in research regarding the precise identification of faulty switches within diverse fault scenarios.
- **Addressing Simultaneous Faults:** The effectiveness of fault diagnosis can be compromised when attempting to identify simultaneous faults across multiple switches. This shortcoming can lead to incorrect diagnoses and the potential delay of vital reconfigurations, emphasizing the need for improved accuracy in handling such scenarios.
- **Holistic Fault Consideration:** The severity of faults showcases significant variations contingent upon fault types, locations, and operational contexts. This underscores the necessity for a fault diagnosis scheme capable of swift and accurate detection, and classification across an extensive range of potential fault scenarios.

Through a comprehensive exploration of existing literature, several gaps have emerged in the current fault detection and localization techniques applied to Multilevel Inverters (MLIs). The traditional model-based strategies, signal processing techniques, and metaheuristic methods have all exhibited limitations in delivering robust fault detection, particularly concerning single and double switch faults. Moreover, the evaluation of these techniques often lacks depth, especially in assessing their performance under various fault scenarios.

Moreover, signal processing methods tend to falter in the presence of signal noise. The need for optimization and transformation methods to enhance the accuracy of fault diagnosis becomes evident. To address these challenges, this study shifts its focus towards AI-based fault detection and localization approaches, harnessing the capabilities of CNN-1D architecture. Outlined below are the key contributions made by this research endeavor:

- The basic purpose of this study is to introduce an innovative approach utilizing CNN-1D architecture for the fault detection and localization process within the context of Cascaded H-Bridge Multilevel Inverters (CHB MLI), so that it can detect both single and double open circuit faults, effectively accommodating a wide array of fault types, their varying locations, and differing operating conditions.
- Excellent results underscore the performance of this method. With high accuracy in detection, efficiency is shown in the identification of the location of both single and double open circuit faulted cases.

This paper presents a deep learning model of the system for the diagnosis of open switch faults in CHB5LIs using only voltage waveform data. The proposed method was based on a CNN architecture that could work to detect a maximum of two faults in switches. It can detect faults of the open switch with high accuracy and may help improve reliability and safety in case of CHB-5LIs under high-power applications.

CHAPTER 3

Methodology & Model of Cascaded H-Bridge 5 Level Inverters (CHB-5LI's)

The chapter gives a detailed discussion of the operational principles and modeling techniques for CHB-5LI's, which are an advanced inverter commonly used in power electronic applications. It starts with the explanation of the theoretical framework underpinning the operation of cascaded H-bridge inverters, with the emphasis on their ability to generate multi-level output voltages by stacking individual H-bridge modules. This chapter also presents a pioneering venture with the application of deep learning approaches to fault detection in such advanced inverters. Integrating the power of artificial intelligence with the intricacies of power electronics, this chapter offers new ways toward identifying and diagnosing faults within CHB-5LIs. In detailed expositions, this chapter elaborates on the ways in which deep neural networks can be trained to recognize patterns characteristic of various faults that could occur in CHB-5LI's. By taking advantage of the vast amount of data that these inverters produce during normal operation, combined with labeled datasets of known fault scenarios, the chapter shows how deep learning models can be highly accurate in fault detection, thus making CHB-5LI-based systems more reliable and robust.

The presenter designed the model by using Keras and TensorFlow. The proposed fault diagnosis approach for open switch fault diagnosis of cascaded H-bridge 5-level inverters (CHB-5LIs) using deep learning includes dataset preparation, convolutional neural network (CNN) architecture, and training and testing procedures. The author used sequential model in our system instead of functional model because it takes only one input and in return yields many outputs, so it was suitable for our system.

3.1 Dataset preparation

Data processing for a Cascaded H-Bridge 5-Level Inverter (CHB-5LI) involves collecting, cleaning, and preparing the data for various purposes, such as fault diagnosis, control, or performance analysis. Below is a general data processing workflow for CHB-5LI data:

Data collection

The dataset used in this study includes voltage measurements taken from single phase of the CHB-5LI. The dataset is prepared by simulating the CHB-5LI under normal and faulty conditions, where a single fault or maximum two faults can occur at the same time. Data is collected from the CHB-5LI system, which includes measurements of parameters such as output and each bridge voltage, and corresponding fault labels. This data is typically captured at regular time intervals during the operation of the inverter.

Sr #	Fault Type	Fault Condition	Combinations
01	Normal	No Fault	01
02	Single switch faults	1 Fault	08
03	Two switch faults	Faulty switch in same leg cases	04
		Faulty switch in diagonal position cases	04
		Faulty switch in upper leg cases	10
		Faulty switch in lower leg cases	10

The data samples for each scenario case contain 80 files for different PWM from 0.55 to 0.95. I have a dataset containing 37 different cases of no fault and faulty switches. The total dataset amounts to 80*37 = 2960 files for various cases. The voltage measurements are preprocessed by normalizing the values to the range [0, 1] to improve the convergence speed of the CNN-1D model during training.

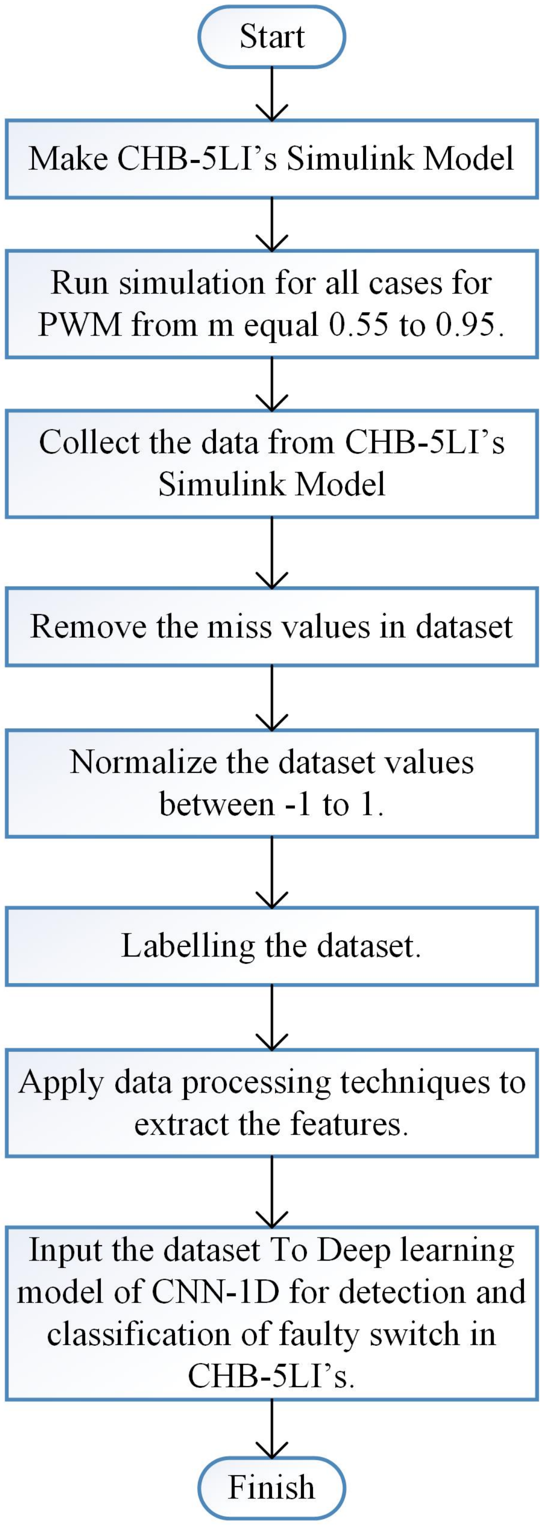


Figure 3.1: Dataset flow diagram

3.2 Data preprocessing

This stage is crucial in fault detection using deep learning for Cascaded H-Bridge 5-Level Inverters (CHB-5LI). The process involves preparing and cleaning the raw data to make it clean enough for training and model optimization. Below is a technical description of the data preprocessing steps.

Data cleaning

A data-cleaning process was carried out to eliminate all inconsistencies, errors, and missing values in the developed data set. This step is very important for the quality and reliability of training data. Missing data points can be imputed by appropriate techniques, such as interpolation or using median/mode values.

Feature extraction

In fault detection, relevant features are extracted from the raw data that best describe the behavior of the system. Such features could be of voltage harmonics, magnitudes, phase angles, or any other such parameters which would indicate the presence of faults in CHB-5LI. This extraction process would bring out important patterns in data, thus reducing dimensionality.

Data normalization

Normalization is the process of adjusting the scales of features to a similar range, commonly between 0 and 1 or -1 to 1. This technique ensures that all features have an equal impact on the training process, preventing any single feature from overpowering the others. Popular approaches for normalization comprise min-max scaling and z-score normalization.

Data augmentation

To enhance the model's robustness and generalization, data augmentation is employed. By transforming the original data—for example, by rotating, flipping, or adding random noise—more synthetic data points are produced. Data augmentation enhances the diversity of the training dataset and also enhances the model's capacity to identify errors in various scenarios.

Data splitting

As part of the model development process, the prepared data is split into training, validation, and testing subsets. The preparation set is applied to adjust the boundaries of the profound learning model, permitting it to gain from the information and work on its exhibition. The validation set plays a crucial role in optimizing hyperparameters, such as learning rates or dropout rates, by evaluating the model's performance on data it hasn't been trained on. Finally, the testing set is managed to measure the ultimate model's performance on unseen data, providing a measure of its generalization ability and effectiveness in real-world scenarios.

Time-series data handling

In cases where the data has a temporal component (time-series data), additional techniques like sliding windows or time-delay embedding may be used to represent the data in a appropriate format for deep learning models.

Dealing with class imbalance

If the fault detection dataset is imbalanced (i.e., some fault classes are more prevalent than others), techniques such as oversampling, under sampling, or using class weights during training can be applied to address the imbalance and prevent bias towards dominant classes.

3.3 CNN architecture

The proposed fault detection (FD) system for the cascaded H-bridge multilevel inverter (CHB MLI) using a 1D convolutional model of neural network (CNN-1D) architecture. The CNN-1D framework is particularly well-suited for sequential data, like the voltage signals collected from the CHB MLI. This architecture leverages the strengths of CNNs while accommodating the nature of time-series data.

The input layer of a CNN-1D processes features like output voltage, individual H-bridge voltages, and switch pair voltages, all obtained from simulation data. The voltage measurements are then preprocessed by normalizing the values to the range of [0,1] to improve the convergence speed of the CNN-1D model during training. These features are sequentially analyzed using 1D convolutional layers. The 1D convolution operation detects temporal patterns and dependencies

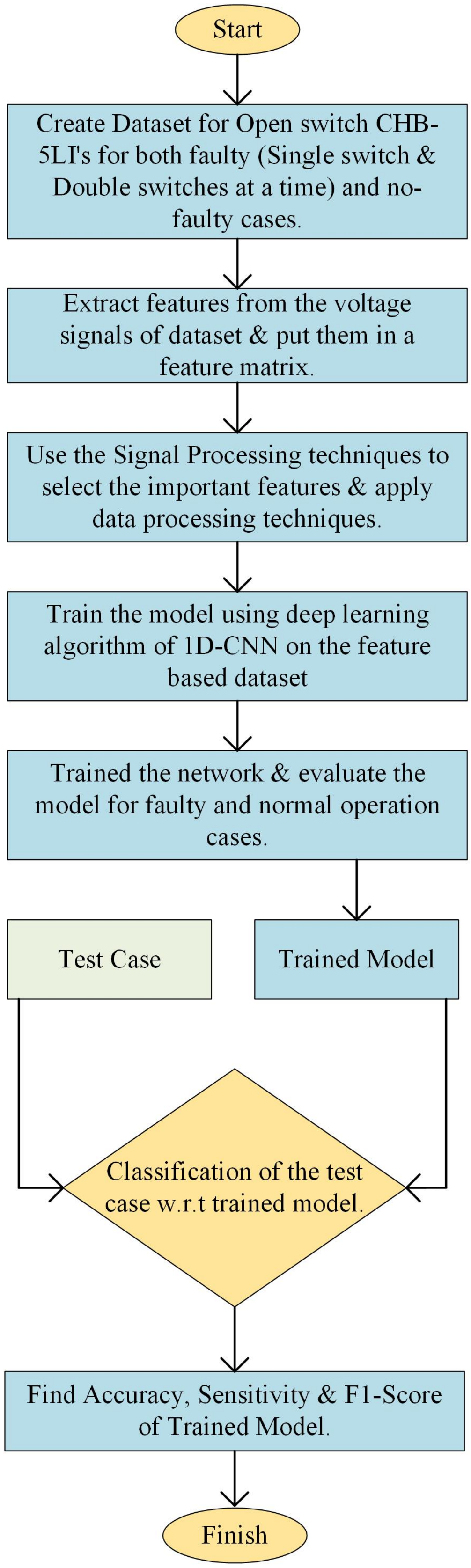


Figure 3.2: Methodology flow diagram

within the data, crucial for fault feature extraction.

In a 1D convolutional layer of a neural network, the output at a particular position is computed by applying a convolution operation to a local region of the input. The general equation for a 1D convolutional layer can be stated as follows:

Given an input sequence X and a set of learnable filters W, the output sequence Y at position i in the convolutional layer is computed as:

$$Y_i = f\left(\sum_{j=0}^{k-1} X_{i+j} \cdot W_j + b\right) \tag{3.3.1}$$

Here:

- Y_i is the output at ith position.
- f is the activation function.
- $\sum_{j=0}^{k-1}$ denotes the summation from $j = 0$ to $k-1$.
- X_{i+j} represents the input value at $i+j$ position.
- W_j is the weight of the filter at jth position.
- b is the bias term.

Following the convolutions, activation functions like ReLU are applied elementwise to the convolved outputs, injecting non-linearity, and enables the network to learn and understand intricate patterns and relationships within the time-series data.

$$f(x) = \max(0, x) \tag{3.3.2}$$

Pooling layers, designed for 1D data, perform down sampling along the time axis. This reduces the computational load and enables the network to focus on the most prominent patterns in time while retaining the pattern's temporal relationship. The formula that is used for the output size of pooling layer is as follows:

$$\text{Output Size} = \frac{\text{Input Size} - \text{Filter Size}}{\text{Stride}} + 1 \tag{3.3.3}$$

The depth of the CNN-1D architecture is decided by the number of hidden layers in the network. In the developed proposal, two hidden layers have been used and each layer has a different filter. These filters exploit different temporal features and help the network to learn fault patterns.

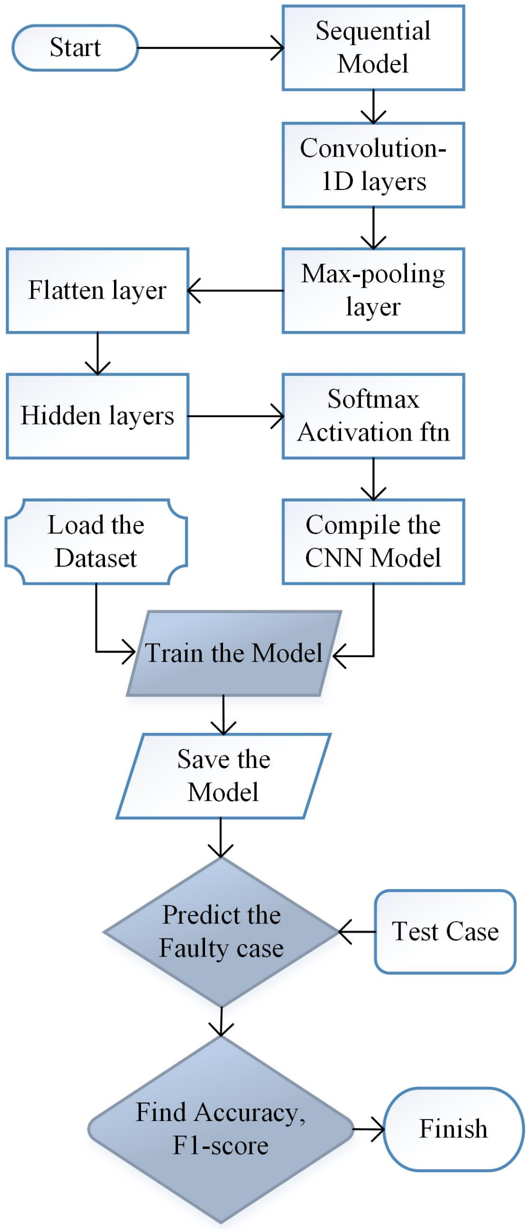


Figure 3.3: CNN-1D block diagram

The next layer is max average pooling, which again simplifies the temporal dimension of the feature maps further while importantly retaining important details, hence it's computationally inexpensive.

The next layers are fully connected, which integrate the learned temporal features for decision making. These layers are helpful in allowing the network to recognize complex patterns within the temporal data and hence make the correct classification of faults.

Finally, there is the output layer, which is activated with appropriate functions and provides classification results. Architecture with CNN-1D along with sequential analysis assists in efficient fault detection and diagnosis in the CHB MLI system.

The proposed architecture of CNN has three convolutional layers, two fully connected layers, and one SoftMax output layer. After every convolutional layer, a ReLU activation function and a batch normalization layer are executed. After the final convolutional layer, the output is flattened and connected to the fully connected layers. Batch normalization layers and ReLU activation functions are provided in the fully connected layers. Fault classification is performed using the SoftMax output layer.

$$\text{softmax}(x)_i = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \tag{3.3.4}$$

This formula defines the softmax activation for an element i in the output vector $softmax(x)$, where x is the input vector and N is the number of elements in the vector.

3.4 Design details

This system is based on 4 convolutional layers, author captured the voltage signal data from the output of the Cascaded H-Bridge 5-level inverter and converted into normalized voltage signal having size of (None, 901) which served as the input for the first convolutional layer, here for this thesis also availed strides of (1) which does not reduce size of voltage data values in addition with valid padding in convolutional layer. In this initial step, the author convolved the given dataset values with the filters and extracted the relevant information from each signal value, after convolutional layer the size of our excel file was (None,899,32). The following are the formulae to calculate the width of convolution layer, here calculate values for first layer:

$$\text{output width} = \frac{W + 2p - k_W}{s_W} + 1 \tag{3.4.1}$$

$$\text{output width} = \frac{901 + 2(0) - 3}{1} + 1 \tag{3.4.2}$$

$$\text{output width} = 899 \tag{3.4.3}$$

Then author applied pooling layer of pooling filter (2) which lessened the voltage signal value size and extracted the information about behavior of output shape of voltage signal, here used maxpooling-1d function, so we get the maximum value of signal from pooling layer window which is applied on the voltage based generated dataset.

After maxpooling1d on first layer our input voltage signal size reduced to (None,449, 32). For this thesis author made 4 layers, after the second layer of convolutional1d our voltage signal size reduced to (None, 447, 64), then we repeated the maxpooling1d step again which further reduced the size of voltage signal to (None, 223, 64). And so, on author made 4 layers. In all the layers, kept the same settings as did for the first layer. After these layers, presenter applied flattening on our 2-dimensional array of data which helped in the conversion of the 2d vector array into 1d layer. After this presenter made hidden layers which interconnected all 1d array with one another by the help of dense function. In the last, dense layer, author defined the number how much output was produced by our system or how many faulty cases in CHB-5LI's for which presenter trained our model, in this layer, also used the Softmax activation function which tells us the probability of most faulty switches case. Presenter can calculate number of parameters for each layer by using this formula:

$$\text{number of parameters} = ((m \times n \times f_1) + 1) \times f_2 \tag{3.4.4}$$

Here:

- m and n represent the width and height of kernel.
- f1 = input layer filter
- f2 = output layer filter

for first layer the number of parameters is:

$$\text{number of parameters} = ((3 \times 1 \times 2) + 1) \times 32 \tag{3.4.5}$$

$$\text{number of parameters} = 224 \tag{3.4.6}$$

Here displayed a table explaining the output size of the system after each layer, and the number of parameters at each layer:

Table 3.1: Model summary

Layer (type)	Output Shape	Param #
layer_conv1d (Conv1D)	(None, 899, 32)	224
layer_max_pooling1d (MaxPooling1D)	(None, 449, 32)	0
layer_conv1d_1 (Conv1D)	(None, 447, 64)	6208
layer_max_pooling1d_1 (MaxPooling1D)	(None, 223, 64)	0
layer_conv1d_2 (Conv1D)	(None, 221, 128)	24704
layer_max_pooling1d_2 (MaxPooling1D)	(None, 110, 128)	0
layer_conv1d_3 (Conv1D)	(None, 108, 256)	98560
layer_max_pooling1d_3 (MaxPooling1D)	(None, 54, 256)	0
layer_flatten (Flatten)	(None, 13824)	0
layer_dense (Dense)	(None, 512)	7078400
layer_dropout (Dropout)	(None, 512)	0
layer_Dense_1 (Dense)	(None, 256)	131328
layer_dropout_1 (Dropout)	(None, 256)	0
layer_Dense_2 (Dense)	(None, 128)	32896
layer_dense_3 (Dense)	(None, 37)	4773
Total parameters of model:	7,377,093	
Trainable parameters of system:	7,377,093	
Non-trainable parameters of system:	0	

3.5 Training and testing

For training, an extensive data set containing both normal and faulty conditions is employed. The dataset is partitioned into training, validation, and testing subsets, enabling the network to generalize well. Backpropagation, in conjunction with optimization techniques like Adam or RMSprop, adjusts the network's weights and biases to minimize the loss, thereby enhancing the network's capacity to detect faults.

The proposed CNN model is trained utilizing the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The training is performed for 50 epochs, and the model with the best validation accuracy is selected for testing. The testing is performed on a separate dataset consisting of voltage measurements taken from the CHB-5LI under normal and faulty conditions.

3.6 Model of CHB-5LI's

A cascaded H-bridge construction is used by the Single-phase CHB-5LI multilevel inverter type to produce a five-level output voltage waveform. This analysis consists of two series-associated H-bridge modules, each of which may produce the voltage levels +Vdc, 0Vdc, and -Vdc. Compared to traditional two-level inverters, the CHB-5LI can synthesize a multilayer output voltage with less harmonic distortion and better voltage quality by regulating the switching states of these H-bridge components. The unique feature of the CHB-5LI is its ability to produce a staircase-like voltage waveform with multiple voltage levels, offering advantages in terms of efficiency, reliability, and performance, mainly in high power applications.

The modeling of the Single-phase CHB-5LI involves developing a mathematical representation of its electrical components and control strategies to accurately simulate its operation. This includes modeling the H-bridge units, the DC-link capacitors, and the control algorithms used to generate the switching signals for each H-bridge unit. The modeling process aims to capture the dynamic behavior of the CHB-5LI under different operating conditions, such as varying load conditions and switching frequencies. Accurate modeling of the CHB-5LI is crucial for understanding its performance characteristics and optimizing its control strategies for several applications, including motor drives, renewable energy systems, and grid-connected power converters.

3.7 Structure and operation of CHB-5LIs

Cascaded H-Bridge 5-Level Inverters (CHB-5LIs) are power electronic systems designed for high-power applications, producing high-quality output voltage with minimal harmonic distortion. The Cascaded H-Bridge Multilevel Inverter (CHB MLI) features a collaborative interplay between the H-bridge modules and the low-voltage DC power sources. This synergy is crucial for adjusting power levels by adding or removing H-bridge modules from the system.

Each H-bridge unit plays a critical role, generating three distinctive output voltage levels: +Vdc, 0Vdc, and -Vdc. This voltage differentiation is accomplished by meticulously manipulating the

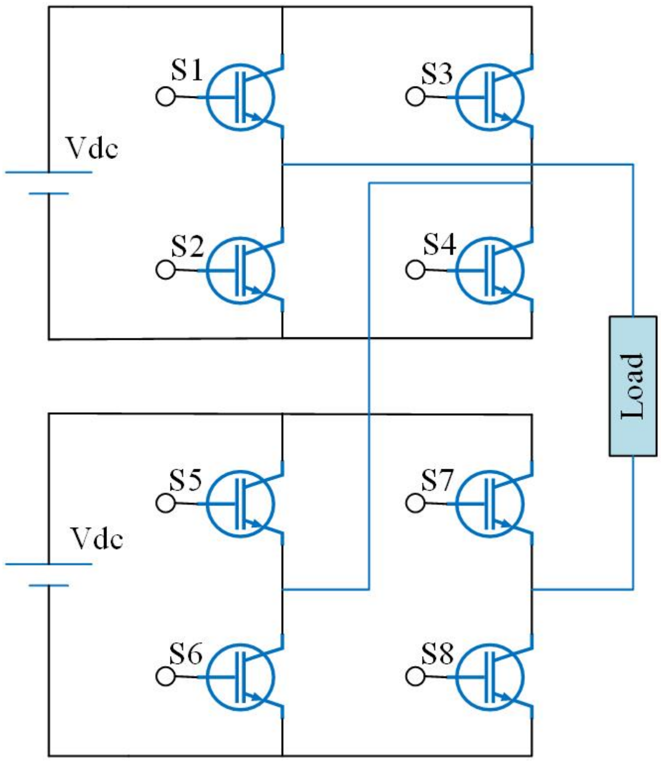


Figure 3.4: H-bridge switch based structure

connections between the direct current (DC) supply and the load. These connections are facilitated through an array of switch configurations, carefully orchestrated to achieve the desired voltage polarity and amplitude.

In essence, the CHB MLI thrives on the harmonious cooperation between the h-bridge modules and the low-voltage DC power sources. This cooperation empowers the system to effectively tailor power levels according to requirements, thereby enabling a versatile and dynamic energy distribution mechanism.

The structure of CHB-5LIs consists of two H-bridge units connected in series, with each H-bridge unit consisting of four switches and a DC source. The number of H-bridge units determines the number of output levels, with each level corresponding to a unique combination of switch states. CHB-5LIs can achieve a maximum of five output levels, hence the name 5-level inverter. The configuration of H-Bridge inverter is shown in 3.4:

The following defines the number of output phase voltage levels, m:

$$m = 2 * s + 1 \tag{3.7.1}$$

where s represents the quantity of distinct DC sources.

Table I. lists the output voltage levels and the accompanying switching states for each. "0" denotes that the matching switch is in the OFF state, and "1" indicates that the related switch is in the ON position [15]. Table I represent the switching state w.r.t Fig.3.1.

Table 3.2: Voltage levels & switching states for CHB-5LI's

Sr #	Output Voltage	S1	S2	S3	S4	S5	S6	S7	S8
01	2V	1	0	0	1	1	0	0	1
02	V	1	0	0	1	0	1	0	1
03	V	0	1	0	1	1	0	0	1
04	0	0	1	0	1	0	1	0	1
05	-V	0	1	1	0	0	1	0	1
06	-V	0	1	0	1	0	1	1	0
07	2V	0	1	1	0	0	1	1	0

Switching various switch combinations is required for CHB-5LI operation in order to provide the required output voltage waveform. pulse width modulation (PWM) is the method used to control the switches. It modifies the width of the switch pulses in order to control the output voltage. The output voltage waveform's harmonic distortion is also lessened by the PWM approach.

The voltage equations for each of the H-bridge modules can be written as follows:

$$V_{\mathrm{ab1}} = V_{\mathrm{a1}} - V_{\mathrm{b1}} \tag{3.7.2}$$

$$V_{\mathrm{ab2}} = V_{\mathrm{a2}} - V_{\mathrm{b2}} \tag{3.7.3}$$

$$V_{\mathrm{load}} = V_{\mathrm{ab1}} + V_{\mathrm{ab2}} \tag{3.7.4}$$

where V_{a1}-V_{b1} and V_{a2}-V_{b2} are the voltages across the first and second H-bridge modules, and V_{load} is voltage across the output load respectively.

To generate PWM signals for a Cascaded H-Bridge 5-Level Inverter (CHB-5LI), we use carrier-based pulse width modulation with a sinusoidal carrier waveform. The carrier waveform generates a high-frequency oscillating signal, while the modulation signal controls the amplitude of the carrier waveform to produce the desired output voltage.

The modulation signal in power electronics systems, such as Pulse Width Modulation (PWM), is commonly generated by comparing the desired output voltage with a reference voltage through a feedback control loop. This control loop adjusts the modulation signal based on the discrepancy between the desired and actual output voltages. Subsequently, the output of the control loop is directed into a comparator circuit, where it is compared with a carrier waveform. This comparison results in the generation of the PWM signal, which regulates the switching of power electronic devices to achieve the desired output voltage or current [4].

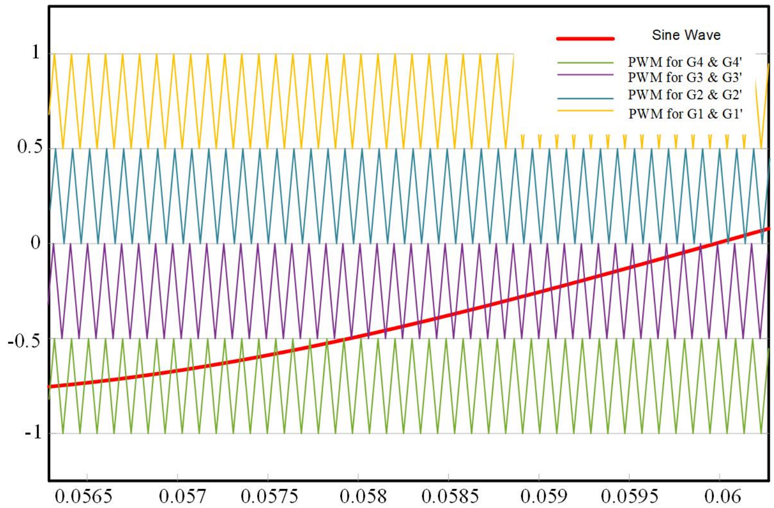


Figure 3.5: PWM generation for cascaded H-bridge 5-level inverters

The modulation index (m) indicates the ratio between the amplitude of the target output waveform and the maximum amplitude of the fundamental output voltage. It can be analyzed as follows:

$$m = \frac{Vref}{Vdc} \tag{3.7.5}$$

where Vref is the reference voltage, and Vdc is the DC bus voltage.

The PWM waveform for each H-bridge module can be generated using the following equation:

$$\text{PWM}(i) = \frac{m}{2} + \frac{m}{2\pi}\sin(wt + d(i)) \tag{3.7.6}$$

where i = 1,2 and di is the phase shift of the ith PWM waveform. The values of di are typically chosen such that the switching frequency of the inverter is constant.

Despite their advantages, CHB-5LIs are prone to different types of faults, which can lead to significant damage to the inverter and the connected load, and even pose a safety hazard in some cases. The different types of faults that can occur in CHB-5LIs include open switch faults, short circuit faults, and capacitor voltage imbalances.

Table 3.3: Fault type for no fault, and single fault.

Sr. No	Fault Type	Fault Mode	No. of Classes	Fault Condition
01	Normal	Fault Free	01	No Fault
02	Single Fault	{S1}	08	Single switch fault
03	(One switch fault)	{S2}		
04		{S3}		
05		{S4}		
06		{S5}		
07		{S6}		
08		{S7}		
09		{S8}		

Open switch faults occur when one or more switches in the H-bridge units fail to operate properly, resulting in an incomplete circuit. This can lead to a high voltage across the faulty switch, which can cause damage to the switch and the connected load. Short circuit faults happen when a direct connection is established between the high voltage and low voltage sides of the inverter, leading to a surge in current that can damage both the switches and the load. Capacitor voltage imbalances occur when there is a difference in the voltage across the capacitors in the H-bridge units, which can lead to unequal sharing of the load and potentially cause damage to the capacitors. Here this paper just focuses on open switch faults with maximum two switches fault detection at a time only.

3.8 Open switch faults (OSFs)

Open Switch Faults (OSFs) are critical faults that can significantly affect the performance, efficiency, and reliability of Single-phase CHB-5LIs (Cascaded H-Bridge Five-Level Inverters). An OSF occurs when one or more semiconductor switches (IGBTs or MOSFETs) in the H-bridge units of the inverter fail to operate properly, resulting in an interruption or open circuit in the electrical path. The analysis of OSFs is crucial for maintaining the optimal operation of the CHB-5LI and preventing potential damage to connected loads.

Table 3.4: Fault type for two switches faulty at a time.

Sr. No	Fault Type	Fault Mode	No. of Classes	Fault Condition
1	Two switches fault	{S1, S2}	04	Same leg switch's fault
2		{S3, S4}		
3		{S5, S6}		
4		{S7, S8}		
5		{S1, S4}	04	Diagonal switch's fault
6		{S2, S3}		
7		{S5, S8}		
8		{S6, S7}		
1		{S1, S3}	10	Upper leg switch's fault
2		{S5, S7}		
3		{S1, S5}		
4		{S1, S6}		
5		{S1, S7}		
6		{S1, S8}		
7		{S3, S5}		
8		{S3, S6}		
9		{S3, S7}		
10		{S3, S8}		
1		{S2, S4}	10	Lower leg switch's fault
2		{S6, S8}		
3		{S2, S5}		
4		{S2, S6}		
5		{S2, S7}		
6		{S2, S8}		
7		{S4, S5}		
8		{S4, S6}		
9		{S4, S7}		
10		{S4, S8}		

Characteristics of OSF

1) Voltage imbalance

In this way, an OSF can unbalance the output voltage levels of the CHB-5LI. A faulty H bridge unit will be capable of providing less level than expected, leading to distorted output voltage waveforms.

2) Current disturbances

For the H-bridge unit where the OSF has affected the proper functioning of the switch, abnormal conduction of current through the inverter can result, increasing the harmonic content and possibly cause damage to the inverter and connected loads.

3) Frequency spectrum alterations

OSFs can introduce new frequency components in the output voltage and current waveforms due to the switching transients and harmonics generated by the faulty H-bridge unit.

3.9 Analysis methods for OSF detection

1) Time-domain analysis

The output waveforms of current and voltage are usually monitored in the time domain so that features and effects of OSFs can be obtained. Some features of OSF, such as voltage unbalance, and waveform distortions, can have signs of abnormalities.

2) Frequency-domain analysis

The harmonic components introduced by the OSF can be found with the help of a frequency spectrum of the output voltage, current waveform analyses, etc. Increased harmonic distortion and new frequency components are some of the features attributed to an OSF.

3) Deep learning-based analysis

Deep learning algorithms, particularly the application of Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), in fault detection are centered on the improvement and enhancement of the accuracy and reliability in OSF detection. Training a deep learning model with labeled data that represents normal and faulty conditions enables the model to learn features or patterns that are particular to the existence of OSFs, which help in correct detection and classification of faults.

3.10 Analysis of open circuit faults

OCFs in single-phase CHB-5LIs can be catastrophic for the inverter performance and reliability. An OCF arises from a failure in one or more semiconductor switches in the H-bridge units, leading to an interruption in the electric path. An OCF in a CHB-5LI introduces voltage and current harmonics, decreases efficiency, and can damage the inverter and load; therefore, good fault detection is required.

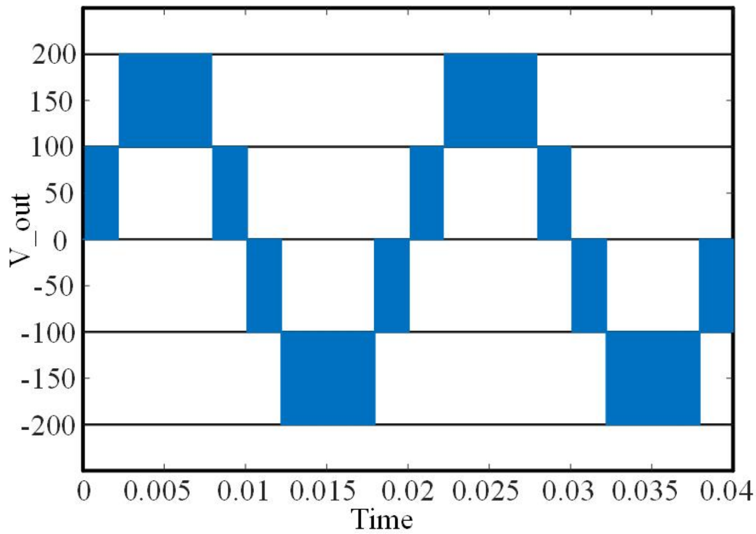


Figure 3.6: CHB-5LI's operate in normal condition output waveform

3.11 Analysis and impact of open circuit fault

If there are no faulty switches and all switches in the CHB-5LI are operating correctly, the inverter will perform optimally and deliver the expected five-level output voltage waveform. In this fault-free state, each H-bridge unit will generate the desired voltage level (+Vdc, 0, or -Vdc) based on the applied control signals, resulting in a balanced and high-quality output voltage waveform. This ideal operation ensures efficient and reliable performance of the CHB-5LI, minimizing harmonic distortion and voltage imbalance, and maintaining the integrity and stability of the electrical system and connected loads. The output voltage waveform is illustrated in the figure 3.6.

3.11.1 Single switch fault

A single switch defect, such as an open circuit fault (OCF) at any of the switches S1 through S8, usually has the effect of lowering the peak voltage. The reduction in voltage can be observed in either the positive or negative levels, contingent upon the location of the impacted switch in the circuit. As a result, the average peak voltage across the system experiences a decrease.

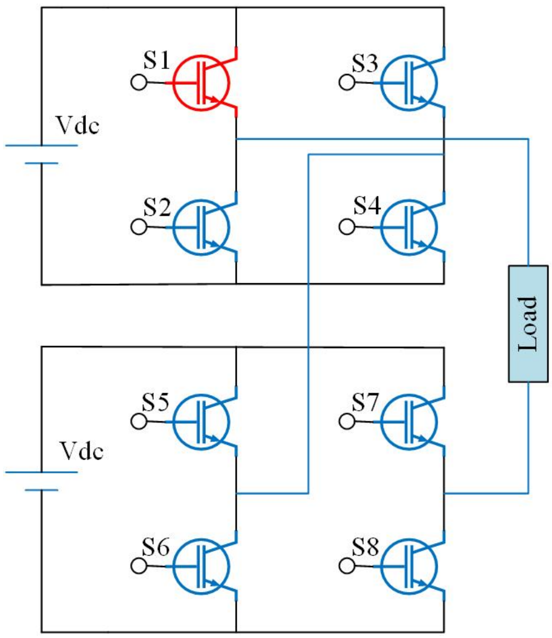


Figure 3.7: Single switch faulty (S1 mark in red)

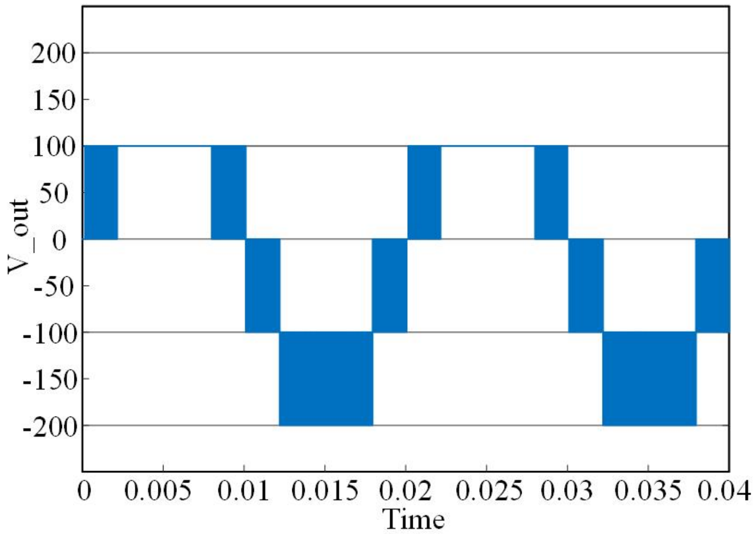


Figure 3.8: Output waveform of single switch S1 faulty

3.11.2 Double switch (DS) fault

The load voltage is clearly impacted by a double switch (DS) failure in the Cascaded H-Bridge Multilevel Inverter (CHB MLI). Reduced voltage levels produce a varied output voltage waveform as a result of this effect. In the context of this study, these DS faults are classified as intricate and multifaceted anomalies.

The instances of double switch fault cases within the primary inverter are systematically organized into three distinct fault classes. This classification approach helps categorize and comprehend the various manifestations of DS faults, contributing to a more comprehensive understanding of their behavior and consequences.

Failure of diagonal switches

Failure of diagonal switches such as switches S1 and S4, or S2 and S3 leading to open-circuit conditions, a notable outcome is the reduction of peak voltage to —— V. The occurrence of a Double Switch (DS) fault in this context introduces an element of asymmetry to the output voltage waveform. This asymmetry results from the unbalanced operation caused by the fault, thereby influencing the overall shape and characteristics of the output waveform.

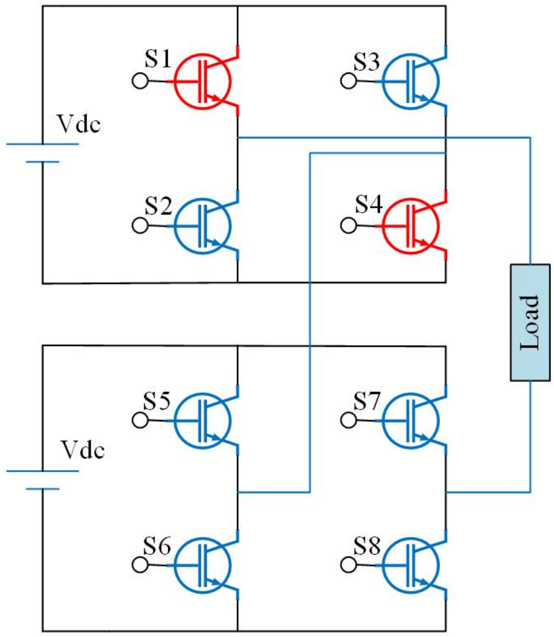


Figure 3.9: Diagonal switches S1 & S4 faulty circuit

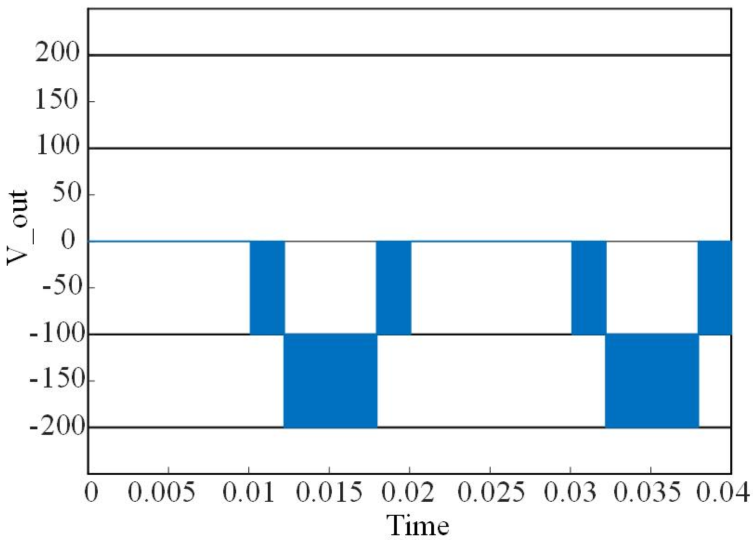


Figure 3.10: Output waveform of diagonal switches S1 & S4 faulty

Upper or lower switches experience a failure

Upper or lower switches experience a failure specifically, switches S1 and S3, or S2 and S4 resulting in open-circuit conditions, a distinct outcome emerges. The peak voltage experiences a reduction to ——- V during both halves of the cycle. Despite the absence of the two voltage levels due to the fault, an interesting observation is that the voltage waveform maintains its symmetry. This means that, despite the fault-induced reduction in peak voltage, the waveform's fundamental symmetry is retained, albeit with altered voltage levels.

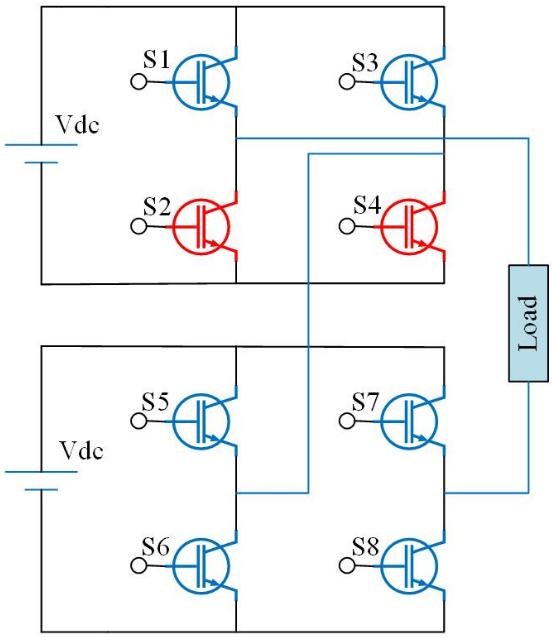


Figure 3.11: Lower leg switches S2 & S4 faulty circuit

The failure of a leg within the system

The failure of a leg within the system, when switches within the same leg experience a fault, leads to a distinct outcome. In such instances, the output voltage becomes nullified. This phenomenon sets this particular type of Open Circuit Fault (OCF) apart from other OCF types. It is clear from a thorough examination that there are significant parallels between the fault features in the output voltage waveforms of leg switches, upper and lower switches, and diagonal switches. Consequently, these fault types are logically grouped together into three distinct categories, based on these shared fault characteristics and patterns.

Detecting and diagnosing faults in CHB-5LIs is essential for ensuring their reliability and safety

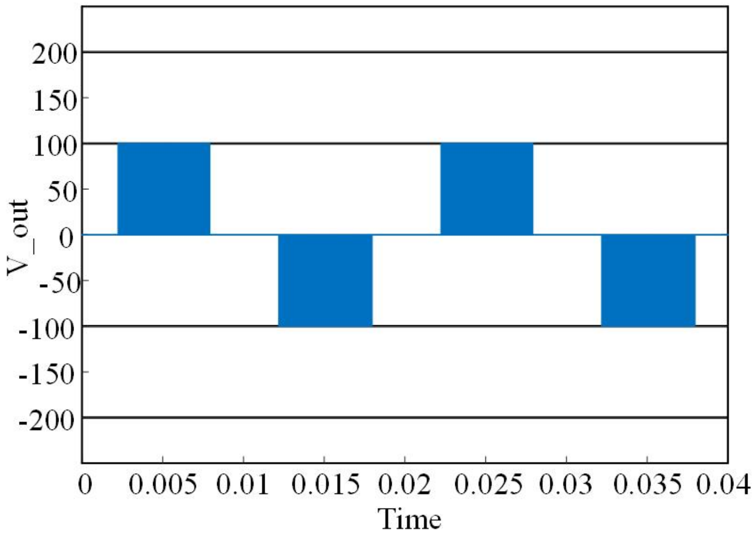


Figure 3.12: Output waveform of faulty lower leg switches case

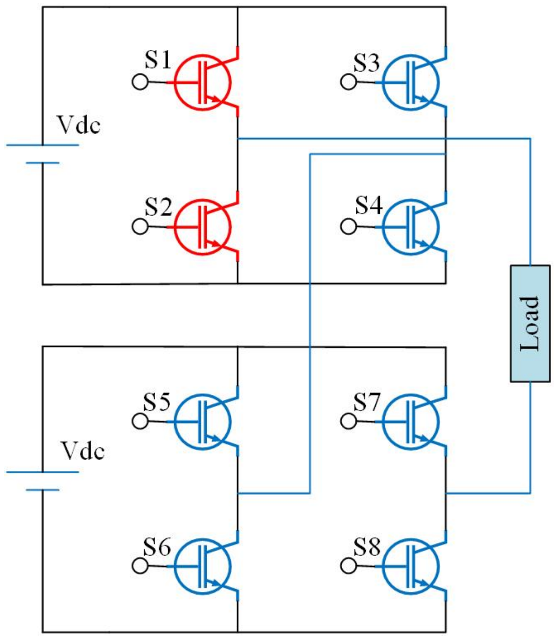


Figure 3.13: Same leg switches S1 & S2 Faulty circuit

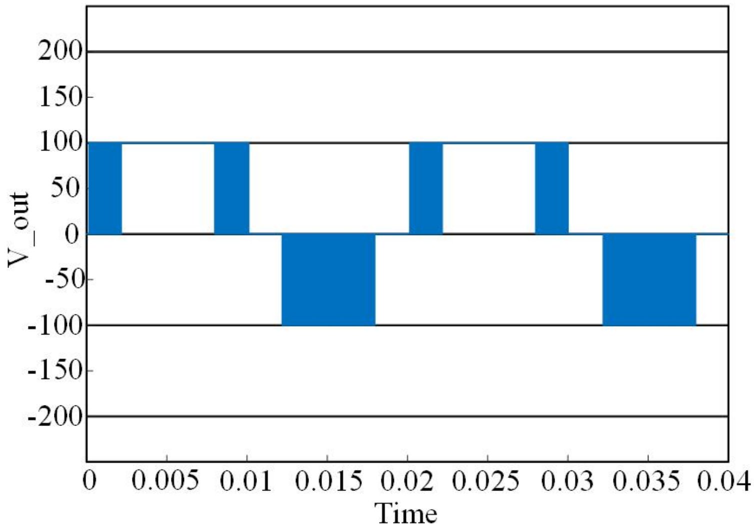


Figure 3.14: Output waveform of same leg switches faulty case

in high-power applications. Traditional fault diagnosis methods for CHB-5LIs typically rely on mathematical models and signal processing techniques, which can be complex and time-consuming. However, recent advances in deep learning-based approaches have shown promising results in fault diagnosis of power electronics systems, including CHB-5LIs.

CHAPTER 4

Proposed Technique Based on Neural Network

Neural networks is recently become popular and are widely used procedure and strategy when it comes to the area of machine learning. A neural network can be basically referred to as a network consisting of numerous neurons which have the function of transferring data from one spot to another spot. These aid in making the machines learn and understand different tasks. The data is received through the input layer and then transmitted to the hidden layers.

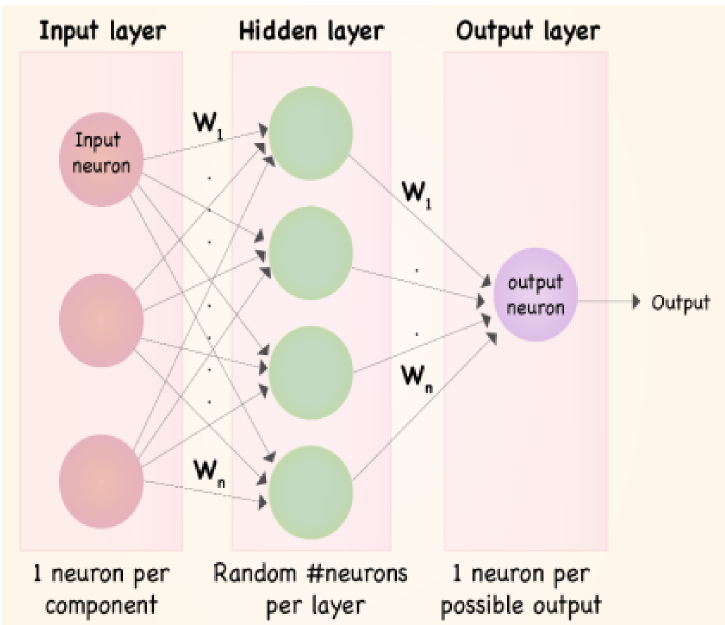


Figure 4.1: Basic neural network model

In these layers, all the processing takes place supplemented with weights and biases. Now the task of an activation function comes. This activation function selects the neurons that should be activated and selects those neurons which should not be activated. Its task is to decide on activating the neurons. After this, the data is passed to the output layer as the last hidden layer is linked with the output layer. The output layer consists of a distinct neuron for each output.

For 1D sample recognition, the process begins with the input of a sample and assigning a label to it, which is called classification if there's only one object, and object detection if there are multiple objects. The next step is featuring extraction, which involves identifying and extracting important features from the sample while ignoring others. This is done using filters that create feature maps by selecting different parts of the sample. The selection of filter size is important as it determines the amount of sample area that is selected at once. Once the feature maps are generated, they are passed through an activation layer, which activates the data, and then sent through a pooling layer to extract relevant parts of the sample while ignoring the irrelevant parts.

4.1 Functioning of neural network

In a neural network, weights and input are multiplied and a weighted sum is calculated afterwards. From this weighted sum, activation function decides whether to activate the neuron or not. If the value of the total sum is greater than the threshold value then it activates the neuron whereas if the sum's value is less than the threshold value, it assigns 0.

Bias – threshold

$$f(x) = 1 if w.x + b >= 0 \tag{4.1.1}$$

$$f(x) = 0 if w.x + b < 0 \tag{4.1.2}$$

$$\sum_j w_j x_j \tag{4.1.3}$$

Also, we can change the value of the weights taken in order to achieve desired outputs. The main agenda of this field is to make the machines perform and perceive data in the same manner as humans do. The advancements in the field of deep learning have been improvised by convolutional neural network.

4.2 Neural network types

The types of neural network are as follows:

- Multiple layered perceptron neural network
- Sequence to sequence models
- Recurrent neural network
- Modular neural network
- Convolution neural network
- Feed forward neural network
- Radial basis function neural network

Feed forward neural network

This type of neural network is consider as popular artificial neural networks type. In the case of feedforward neural network, the information is transmitted via the several nodes of input until this data approaches the node present at the output. In other words, the information moves in a single path, which means information moves from frist node till it approches the output node. This is also referred as a front propagated wave which is in most cases attained by utilizing an organizing activation function. In most neural network no backpropagation is present and the information is carried in a single path hardly. A feedforward neural network might comprise of one layer only, or hidden layers maybe supplemented. In this neural network, a total value from the yields of the inputs and their weights are estimated and calculated. This total value is then provided to the outcome. Below is an instance of a uni-layer feedforward neural network.

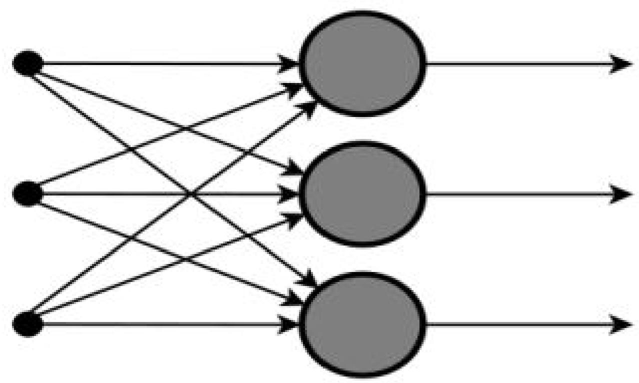


Figure 4.2: Feed forward neural network model flow

Feedforward neural networks have applications in face recognition and also in computer vision areas. This is due to the reason that the target classes are difficulty identified in these applications. A basic network of this kind is skilled to deal problem which comprises of a lot of distortion and noise. These networks are also comparatively easy to keep.

Radial basis function neural nets

A radial basis function reflects the length of any spot relative to the middle point. These neural networks consist of two layers. Talking about the innermost layer first. In the case of this layer, features are mostly mutually attached with function of radial basis,after which output arrives. The output is described when estimating can analyze the output which is same in the next move. Below the figure depicts radial basis neural network.

Figure 4.3: Radial basis function network model

The network has wide applications in power restoration system areas. Recently, its said that power systems are becoming wider and more complicated. An overveiw of this fact enhances any dangers of backouts. This network has applications in power restoring systems so that it could help in reestablishing power.

Multiple layered perceptron neural nets

A multilayer percepton consists of three layers or above it is utilized in figuring information that is not capable of being divided linearly. This form of network is completely linked. This is because node in a its respective layer is connected to node next to it. It makes use of an activation function which is non linear in nature. Below is a multilayer perceptron neural network represented:

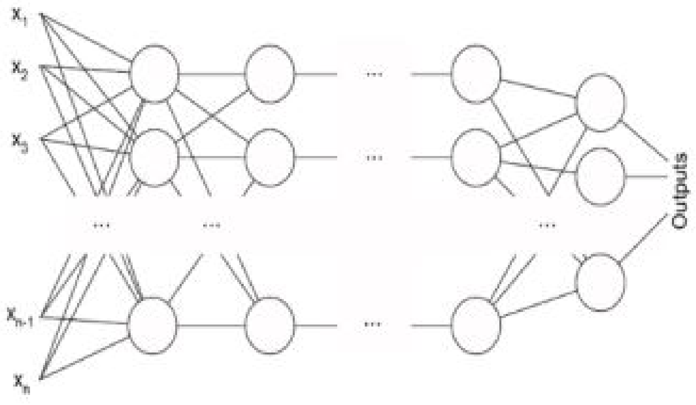


Figure 4.4: Multiple layered perceptron neural network model connections

This form of neural network has extensive applications in recognizing the voices and in skills of machine translation.

Recurrent neural network

It is a type of artificial neural network where the output of a particular layer is prevented and fed back into the input. This helps in achieving more accurate predictions related to the layers. In this case, the creation of the initial layer takes place in the same manner as in case of a feedforward network. This means, a combination of the summation of the weights and features. However, in following layers, the recurrent neural network method starts. Starting from a single time-step to the stage ahead it, each node is capable of storing information linked with its previous time-step. This means that each node present functions as a memorial cell while executing functions. The network starts from propagation of the front. It keeps the data which is needed for later purpose. In case the forecast made by this system is incorrect, it comprehends it and also learns on its own about its wrong match and functions towards making the correct guess during the backpropagation.

Modular neural network

This form of network made up of various different network and these can also function parts of tasks. There is no coordination of diverse networks among each other and no messages are sent during the method of calculation among one another. They function independent of each other and are self reliant in attaining the result. Consequently, a great and complicated calculation method can be finished quicker by splitting these into self reliant halves. The pace of calculation rises when the networks stop working with each other or become linked with each other. Below is provided a pictorial representation of this network.

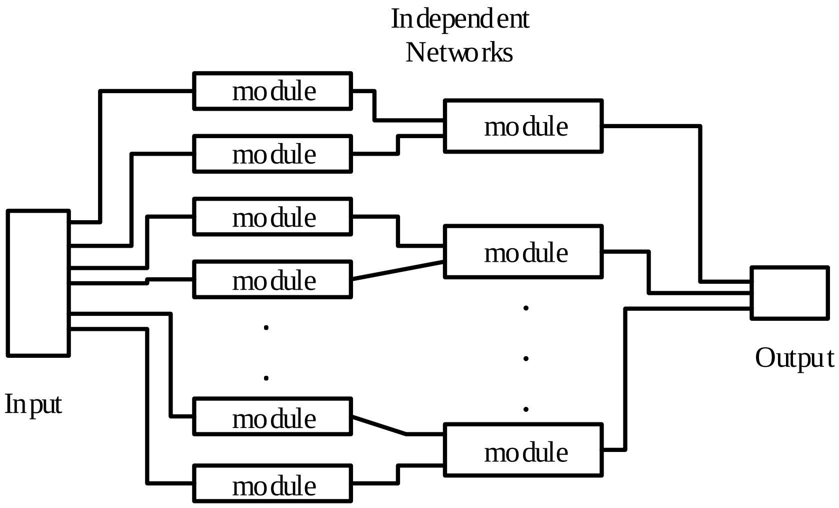


Figure 4.5: Modular neural network model structure

Sequence-to-sequence models

The next Model is sequence to sequence. There are twice recurrent networks in this network. Also, an encoder is there which is capable of practicing the input and a decoder which practices the outcome. These decoders and encoders present either avail the same paramters or the unlike ones.This network has applications specifically in the fields in which the size of the input information is not exactly same with the output information length. This network is used in chatbots, translation of machinery and also in systems involving questioning answering.

4.3 Keras model

Keras is an open-source neural library under which other libraries such as TensorFlow etc. can be run, and it is designed to run fast practical.

There are two ways to execute Keras models which are as follows:

- Sequential API
- Functional API

Sequential API

This model lets you design models in a sequence i.e., layer after layer. It cannot have multiple inputs. This model consists of a stack of layers connected one after the other between input and output. It is remarkable for deep learning models. A sequential model helps to establish the model in the form of layers, where one layer comes after the other and these are present in a sequence. These can produce multiple outputs.

Sequential model of Keras API is a method of making deep learning models. In this basically a sequential class is synthesized, and more layers can be added to it. These layers are passed as an array in a sequence.

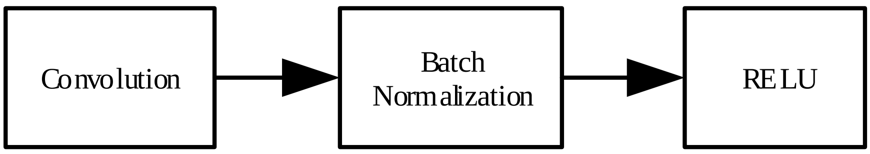


Figure 4.6: Sequential API flow

Functional API

In this model the layers connect not only to the layers one after the other but in this model the layers can be connected to any other layer. Here there is no restriction of connecting to the previous and next layers only. It can have multiple inputs and outputs. As a result, it forms a complex network. It allows the layers to connect not only to their previous layers but to any layer present.

Therefore, we preferred to use the sequential model as it can have multiple outputs and the input used is one which is suitable for our project.

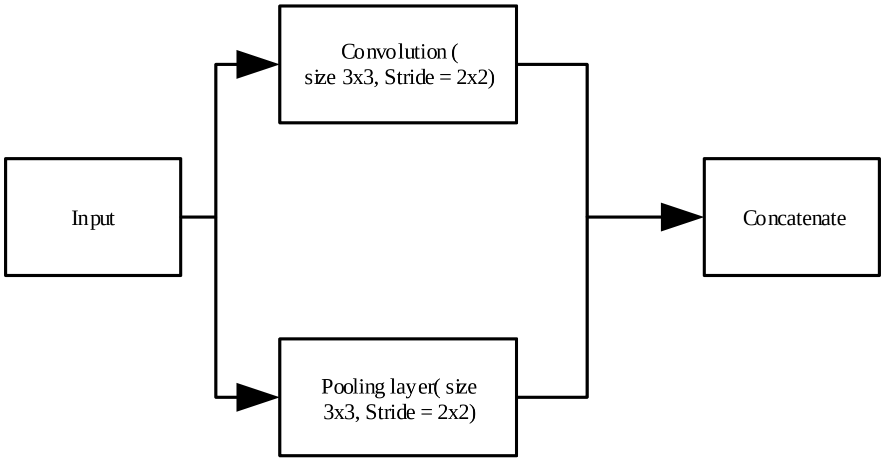


Figure 4.7: Functional API flow

Data preparation

Data is prepared in such a way that the network can train it. This includes gathering samples of time vs voltage from CHB-5LIs model and tagging them different labels based on fault condition. The main thing is the time the model takes to get trained. This is done by setting epochs.

Model evaluation

In this the model is compared with a dataset. The dataset contains numerous samples belonging to different classes.

Why we used CNN?

We used CNN as it helps in classification of different fault condition in CHB-5LIs. The main reason to use it was that when we compared the real time samples with CNN, it provided the results with high accuracy. Also, its more powerful than RNN. It leans various features. This is suitable for large datasets.

4.4 Convolution neural network (CNN)

Artificial neural networks (ANNs), a crucial component of machine learning, are engineered to replicate the structure and functions of the human brain. Each unit in the network, which is made up of interconnected neurons, performs non-linear calculations on inputs, frequently derived from the neurons' outputs in the layer above. The backpropagation procedure, which improves the prediction accuracy of the model by iteratively adjusting the network's parameters to minimize the difference between expected and actual outputs, is the foundation of ANN training.

A typical artificial neural network architecture generally includes three primary layers: first one is the input layer, in the middle network have one or more hidden layers, and at the last an output layer. In Figure 4.8, the input units are denoted as x, the model hidden units as h, and the output units as o, demonstrating the information flow through the network. This model is commonly used for classification tasks, where the input data is processed through the network to produce a corresponding output. During forward propagation, the input to the neural network is passed through each layer, with computations performed at each neuron, ultimately resulting in an output. The defined loss function and the optimization algorithm define a mapping from input to output. These are then applied to adapt the network parameters during training.

During the training phase of ANN models, weights are basically revised to reduce the loss function; thereby, optimization is necessary in order to improve the network's capacity for better and precise predictions. In the validation stage, k-fold validation is one of the most frequently used practices to evaluate the performance of ANNs. Data are divided into k subsets in k-fold validation and the system is trained k times, each time using a different subset for validation. This process helps to understand the generalization ability of the model, taking into consideration how well it performs on diverse data subsets. The standard ANN structure, comprising input, hidden, and output layers, utilizes backpropagation for training. The mapping of input to output during forward propagation is guided by a loss function and optimization algorithm. The iterative weight updates aim to minimize the loss, and performance evaluation commonly involves k-fold validation to ensure robust generalization.

While artificial neural networks (ANNs) exhibit effectiveness in addressing certain challenges, they grapple with two primary issues. Firstly, the limitations of shallow neural networks, characterized by few hidden layers, become apparent when confronted with intricate problems. To enhance performance, a remedy involves employing deeper networks with more hidden lay-

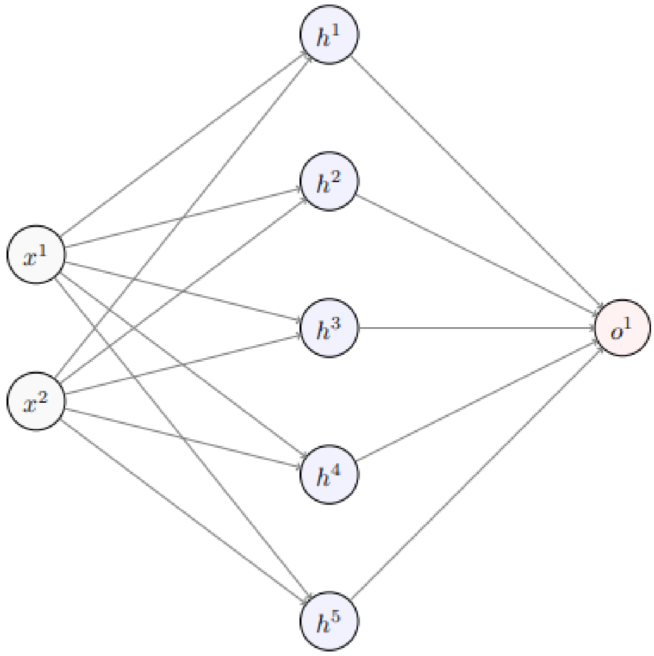


Figure 4.8: A basic ANN model comprises an input layer, a hidden layer, and an output layer

ers. However, the drawback lies in the complexity of training deep neural networks due to the occurrence of vanishing gradients.

The challenge intensifies when dealing with high-dimensional inputs, such as image datasets, where the selection of optimal features becomes crucial. Failure to extract the most relevant features can lead to overfitting of the ANN to the data. Optimally extracting these features is a manual task, and the complexity increases when it comes to manually curating feature selection. The problems encountered in ANNs include the fact that shallow networks are not up to complicated problems; they require deeper networks, and there arises the problem of the difficulty entailed in training them because of vanishing gradients. The second challenge is to choose optimally the features from high-dimensional inputs, especially from datasets containing images, so that danger from overfitting can be reduced.

The second challenge is effectively overcome by convolutional neural networks through an extremely smooth interface for feature selection. They manage to do this by baking in the idea of convolutional layers, which cuts down tremendously on the work that would have been done by hand in the curation of features. In most cases, CNNs use a fewer number of neurons because of weight sharing over multiple convolution outputs, making them computationally efficient and increasing optimization.

Basics of 1D CNN

Convolutional neural networks come within the domain of Deep Learning: it is that branch of machine learning where multi-layered artificial neural networks are used to provide state-of-the-art accuracy in a wide range of tasks, from language translation to object detection. The turning point for CNNs was when one of their models won the LSVRC-2012 (ImageNet) competition and had performed remarkably well. CNNs are designed to transform 2D inputs into real values for regression-based tasks or categorically into outputs for classification problems.

This chapter is an attempt to delve into 1D CNNs. A typical CNN model has two basic types of layers, illustrated in Figure 4.9:

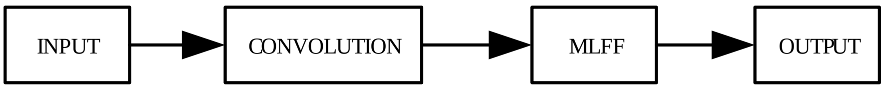


Figure 4.9: A typical CNN structure

- Convolution Layers: At the core of data processing, convolution layers play a crucial role by employing convolution operations to analyze input data. These operations capture local patterns and features, enabling the network to discern hierarchical representations within the input.
- multi-layer feed forward (MLFF) Layers: Sequentially following the convolutional layers, MLFF layers take charge of additional processing of the extracted features and play a key role in generating predictions. These layers significantly enhance the network's capacity to comprehend intricate relationships and patterns within the data.

In the subsequent sections, we will deep-dive into how forward and backward propagations occur in both convolution and MLFF layers. That elaboration is done because one needs a very clear understanding of information flow inside the network both at the training and prediction phases. This is actually quite important in effective CNN training to exploit the potential of these networks on various machine learning tasks.

Forward propagation

The convolution layer is the next layer of neural networks in order following the input layer. A convolution layer plays the role of a feature extractor [34]. The output passed by the convolution layer finally flows to the MLFF network. In fact, the convolution layer actually executes some operations on the input like the convolution (or correlation) operations, as well as some other relevant procedures, and therefore acts as a feature extractor. On the other hand, the MLFF network serves as a decision-making block for determining the class of the input or making any kind of prediction based on features that are extracted by the previous convolution layer.

4.5 Convolution layer

Convolution, also known as the shift compute operation, is the process of sliding the kernel across the input signal. There are two ways to carry out this operation:

- Convolution that is not causative - Making use of cross-correlation, which is frequently used in traditional CNNs
- Convolution with causation

The subsequent subsections delve into the distinctive characteristics of both types of convolutional layers, while also addressing crucial operations like pooling, activation functions, and other pertinent aspects.

Non causal convolution - correlation

According to conventional Digital Signal Processing (DSP) textbooks, cross-correlation is equivalent to non-causal convolution. Since the output, represented by the letter out, depends on incoming data in the future, it receives the "non-causal" descriptor. In practical terms, a system is considered non-causal if its output (out(0)) depends on an unknown future input (in(1)).

Consider a kernel with lengths of k, and h, respectively, with an input of length l, in. The convolution function shifts the kernel window by s positions, or the specified number of strides, after every iteration. Thus, the non-causal convolution between in and h for a given stride s is determined accordingly as follow:

$$out(l) = \begin{cases} \sum_{i=0}^{k} in(l+i)h(i), & \text{if } l = 0 \\ \sum_{i=0}^{k} in(l+i+(s-1))h(i), & \text{otherwise} \end{cases} \tag{4.5.1}$$

For example, if l = 5, k = 3 and s = 1 then

$$out(0) = in(0)h(0) + in(1)h(1) + in(2)h(2)$$
$$out(1) = in(1)h(0) + in(2)h(1) + in(3)h(2)$$
$$out(2) = in(2)h(0) + in(3)h(1) + in(4)h(2)$$

Notably, the output length of this convolutional mode which Keras refers to as the "valid" mode does not match the input length. To get the required output length that is identical to the input length, padding might be used. In Keras, this specific mode is referred to as the "same" padding convolution.

$$o = l \tag{4.5.2}$$

For a particular stride s, the length of the output, indicated as o, in the "valid" mode and without padding is calculated as follows:

$$o = \left\lfloor \frac{l-k}{s} \right\rfloor + 1 \tag{4.5.3}$$

Considering an input of size l, a kernel of size k, and padding of size p [34], the length of the output after padding is expressed as follows:

$$o = \left\lfloor \frac{l+2p-k}{s} \right\rfloor + 1 \tag{4.5.4}$$

Causal convolution

In this type of convolution, the result is independent of subsequent inputs. Think of a kernel, denoted by h, with a length of k, and an input to the convolution layer, represented by in, with a length of l. The kernel window is moved by s places, or the number of strides, following each convolution step. The causal convolution between in and h is therefore defined as follows for a given stride s:

$$y(n) = \begin{cases} \sum_{i=0}^{k} out(l-i)h(i), & \text{if } l = k-1 \\ \sum_{i=0}^{k} out(l-i+(s-1))h(i), & \text{otherwise} \end{cases} \tag{4.5.5}$$

Causal convolution has the same output length as non-causal convolution and can be used with or without padding options. Let's look at an example where there is no padding[26], with l = 5, k = 3, and s = 1. The convolution operation in this instance can be written as:

$$out(2) = in(2)h(0) + in(1)h(1) + in(0)h(0)$$
$$out(3) = in(3)h(0) + in(2)h(1) + in(1)h(0)$$
$$out(4) = in(4)h(0) + in(3)h(1) + in(2)h(0)$$

Evidently, out is devoid of reliance on future inputs, establishing its causal nature. This causality allows for conceptualizing the kernel weights as the impulse response, a convention often denoted by h. In this context, the representation aligns with the conventional practice of using h to represent the impulse response.

$$out(n) = in(n) * h(n) \tag{4.5.6}$$

It is possible to determine the system's output for any input by knowing the impulse response h(n) [26]. Convolution does, in fact, correspond to multiplication in the frequency domain in the time domain. The frequency domain expression for the aforementioned equation is as follows:

$$OUT(f) = IN(f) \cdot H(f) \tag{4.5.7}$$

Relation between causal and non-causal convolutions

Taking into account Equation 4.5.1 for s = 1, it can be expressed in terms of Equation 4.5.5 as follows:

$$out(n) = \sum_{i=0}^{k} in(l+i)h(i) = \sum_{i=0}^{k} in(l-(-i))h(-i) \tag{4.5.8}$$

Let $j = -i$.

$$out(n) = \sum_{j=0}^{k} in(l-j)h(j) \tag{4.5.9}$$

This can be reformulated in the context of convolution as:

$$out(l) = in(l) * h(-l) \tag{4.5.10}$$

The Fourier Transform for the aforementioned equation is expressed as:

$$OUT(f) = IN(f) \cdot H^{*}(f) \tag{4.5.11}$$

Equations 4.5.11 and 4.5.7 are used to show that the phase responses of the causal and non-causal convolution outputs differ only in magnitude, and that the frequency responses for both are the same.

$$|OUT(f)| = |IN(f)H(f)| = |IN(f)H^*(f)| \tag{4.5.12}$$

During the analysis of filters, it becomes evident that the phase component holds minimal significance. Consequently, the choice between a causal or non-causal filter becomes inconsequential. Notably, if the kernel weights are such that out(l) equals out(-l), the convolution operation is equivalent to correlation.

4.6 Pooling layer

Pooling is used to highlight important features while reducing the dimensionality of a given mapping. It is usually added after the convolution layer and is essential for minimizing overfitting and lowering the convolution output's dimension. Max pooling is one of the most used pooling strategies. When using max pooling, the largest value inside a window of size f is chosen, and after each pooling operation, this window is gradually moved over the input with a stride of length s.

4.7 Flatten

The role of flatten is quite easy. Its involved in reshaping the tensor in such a way that it becomes equal to the number of elements contained. Also, it helps us in adding layers in a sequence when we use sequential model. It takes 2-dimensional data of one shape and gives 1-dimensional data of another shape as an output. It doesn't change the data but only the shape of the data. By the word flatten in a tensor we mean that we are lowering the rank of a tensor. We take the output from a convolutional layer provided to us in the form of channels and then we flat these channels i.e. convert these to 1-dimensional.

4.8 Full connection

Dense layer

Flatten is there as a medium between the convolution and dense layers. Dense is basically a standard layer which is used in neural networks. It's the layer used for output layer. Dense in Keras indicates a fully connected layer. It's a regular densely connected neural layer. It's a dot product between the input and the kernel, where kernel is a weight matrix. Dense layers are responsible for carrying out classification based on the features extracted from the convolutional layers. In dense layers every node relates to each previous layer node.

A dense layer consists of neurons and also its regarded as an orderly and unvarying sheet. Here, every neuron gets information from the neuron present behind it. This layer has 3 elements, an activation function a , a weight matrix W and a bias b. it's a fully/densely connected layer. It's given by

$$\mathrm{output} = \mathrm{activation}(\mathrm{dot}(\mathrm{input}, \mathrm{kernel}) + \mathrm{bias}) \qquad (4.8.1)$$

where[33]:

- activation is the activation argument
- kernel is a weight matrix
- bias is a bias vector

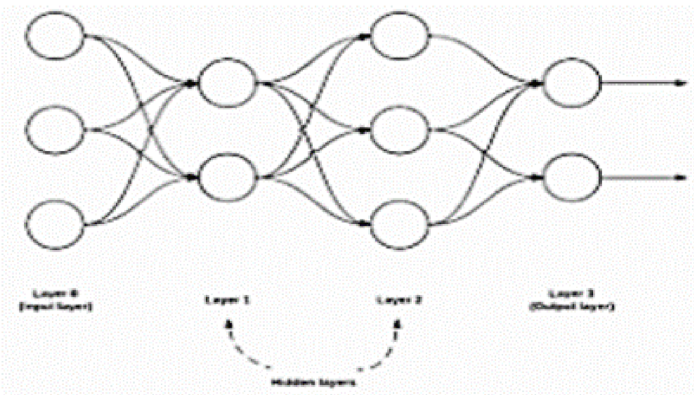


Figure 4.10: Dense layer connections

In dense layer the arrows move only in the forward direction and in one direction.

Drop out layer

Drop out layer helps in avoiding over fitting. If the value of dropout is for example 0.3 then it means that we have used 30 percent of the neurons. It helps us into getting insight in learning. The model learns better. It works by randomly adjusting the outgoing edges. It trains many neural networks with different outlooks. During this a few numbers of layers are dropped out. Drop out is applied on the hidden, visible, input layers but not on the output layer.

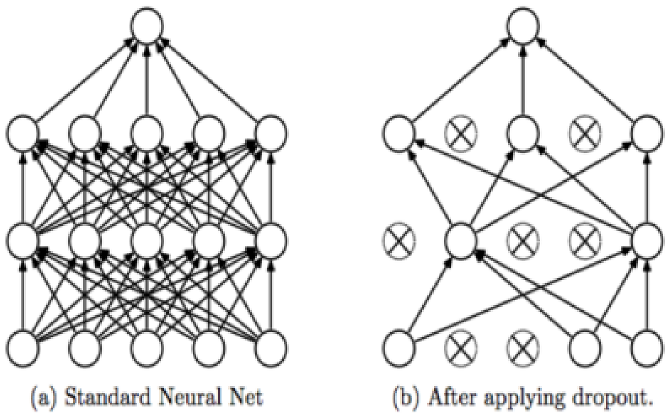


Figure 4.11: Dropout function outcome

4.9 Hidden layers

Hidden layers are layers having mathematical functions each generating a specific output. Each hidden layer generates a defined result. As these layers are not directly visible and are situated between the input and the output layers, they are indicated to as hidden layers. The total number of hidden neurons should typically fall between the sizes of the input and output layers. It must have a value less than 2 times the input layer size. There can be 0 or more hidden layers in the network. In these there are inputs having weights and output is produced using an activation function. While in some cases, they are tuned by the method of backpropagation. These hidden layers convert the input into desired output. Now consider we have two functions. One function f map from x(input) to h (hidden layer). And another layer maps from h to y(output). Here the activation will be f(x) and the output produced will be g(f(x)). This generated output g(f(x)) will have even those functions that f and g will not have alone.

4.10 Activation functions

These are the mathematical formulas that determine a neural network's output. This function determines which neurons should fire (be activated) and which ones should not. It is associated with every neuron. These also bring the output of each neuron within the range of 0 and 1 or ¬1 to 1. These serve as a mathematical gate between the input and the output which is to be produced. These are dependent on a threshold value to switch a neuron on or off. Mostly, non¬linear functions are utilized for accurate results.

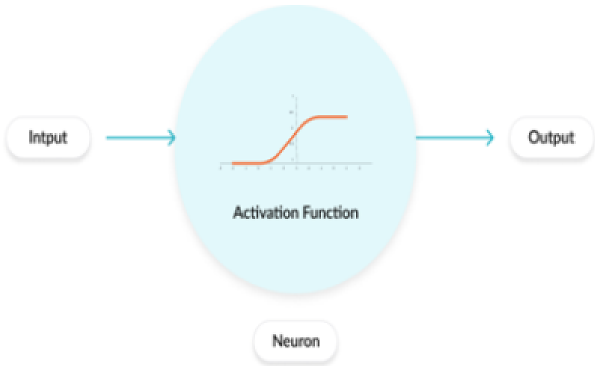


Figure 4.12: How activation function performs

$$Y = \text{Activation}((\text{weight} \cdot \text{input}) + \text{bias}) \tag{4.10.1}$$

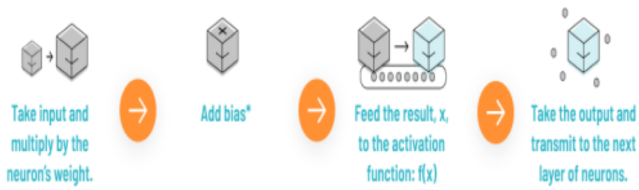


Figure 4.13: Activation process

There are 2 types of activation functions.

- Non Linear Activation Function;
- Linear Activation Function;

We use non-linear activation function Relu for training of our model.

Relu

Among the non¬linear activation functions types, the rectified linear unit (ReLU) function is mostly used. Since, it is utilized in almost all the CNNs. As it can be noticed, the Relu function is half rectified.

- f(z) is equal to zero when z has a value less than zero
- f(z) is equal to z when z has a value either greater than or equivalent to 0.

This function ranges between zero and infinity.

But here, the main problem is that all the negative values become equal to 0 instantly as a result of which the capability of the model or the system to fit, comprehend or train from the information appropriately, lessens. This implies that any input having a negative value given to the Relu activation function converts that value into 0 instantly in the graph, as a result of which the final chart is affected by not mapping the integers which have a negative value, properly.

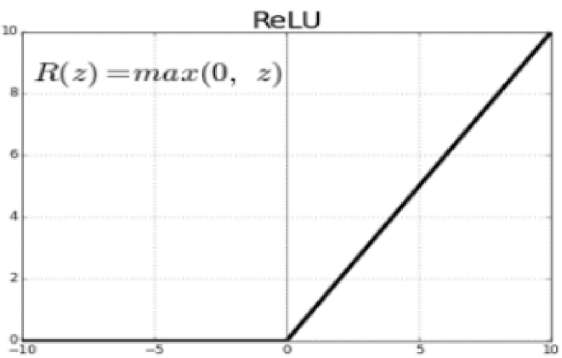


Figure 4.14: Relu activation function curve

This function is presented by

$$F(x) = \max(0, x) \tag{4.10.2}$$

Softmax

The Soft Max function takes an input vector comprising of real numbers and normalizes this vector into a probability distribution. When we use the vector, some components could be either positive, some could be negative but after we apply SoftMax function each part will range between 0 and 1. Moreover, the components will sum up to 1. SoftMax is utilized to normalize the non¬normalized outcomes. It maps the non¬normalized outcomes in the form of probability distribution. It estimates the probability distribution of a specific event over the total events.

It also estimates the losses that could be faced and their probabilities.

It's a combination of various sigmoid functions. The quantity of neurons present in the output layer can have the same value as the classes present. It's useful for multiclass recognition problems.

4.11 Compiling model in keras

Compile in Keras is only to define the loss functions, the metrics and optimizer. It asks us the type of optimizer we want to use and also about the loss function. If we compile a model again, we the optimizer states will be gone. In order to train our model what we do is we use compile. In this step, we determine the structure of the model, which includes specifying the number of hidden layers and the activation functions to be used.

4.12 Optimizers

Optimizers are used to compile a Keras model. These support in decreasing error functions. These reduce the error functions by altering the weights.

The goal of the machine learning algorithm

Its found that the aim of machine learning and deep learning is to diminish variance factor present among the original and foreseen outcome. This can be termed titled either cost or loss function. Cost functions are out curved. Here, the supreme aim is to calculate the adjusted integers of weights and also to reduce cost function value. Here, the simplification of the algorithm is also important. This will aid and support in making an improved expectation for the data that was not looked up before.

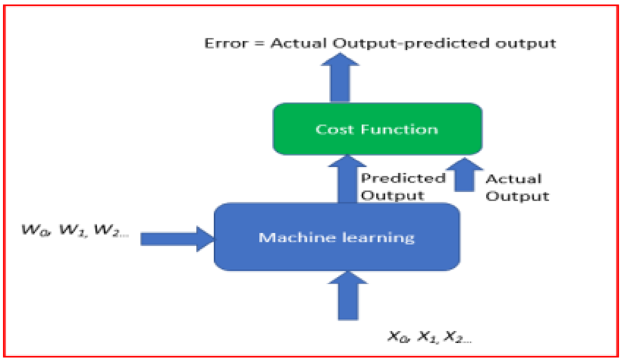


Figure 4.15: Machine learning algorithm

4.13 Gradient descent

gradient descent (GD) is termed as a frequentative advanced algorithm for machine learning that helps in reducing the value of cost function. This aids the structures capable of making precise forecasts.

Gradient notifies us about the track of increase. We move in the opposite path of the gradient because we want to calculate and identify the valley's minimum spot. Also, the parameters are updated in the gradient track having a negative value in order to reduce the loss as much as possible.

$$\theta = \theta - \eta \nabla J(\theta; x, y) \tag{4.13.1}$$

Here θ refers to the weight parameter, η refers to the rate of learning and J refers to the weight element of the gradient.

Gradient descent types

Gradient descents' various types include:

- Stochastic gradient descent
- Mini batch gradient descent

- Batch gradient descent

Batch gradient descent

In this case, in order to calculate the cost function's gradient for every iteration and also then to update weights, the whole dataset is utilized.

As the whole dataset is utilized, the convergence of gradient becomes sluggish.

In case there is a large the dataset having millions of data points, then it is memory and computationally concentrated.

Temp.	Visibility	Actual o/p	Predicted o/p
73	10	1	0
50	2	1	1
32	1	0	1
80	5	1	1
23	.1	0	1

Update w_i

Batch Gradient descent

Figure 4.16: Batch gradient descent table

This gradient avails the whole data set so that it can compute every single iteration of gradient descent.

Advantages of batch gradient descent

- Examining weights theoretically
- Rates of convergence are easily comprehended

Disadvantages of batch gradient descent

- Perform excess calculation for a similar preparing model for huge datasets
- Also has slow speed and becomes inflexible in case huge datasets do not accumulate in memory

- The weights can be updates for every new information when the whole dataset is calculated

Stochastic gradient descent

The next is stochastic gradient descent (SGD). In this, only one information data point is used. This can be explained by an example of computing the gradient and then updating the weights for every single iteration.

Firstly, the dataset needs to be shuffled. This is done in order to attain a completely random dataset. After updating the weights and making the dataset random, the cost function becomes noisy. This is illustrated below

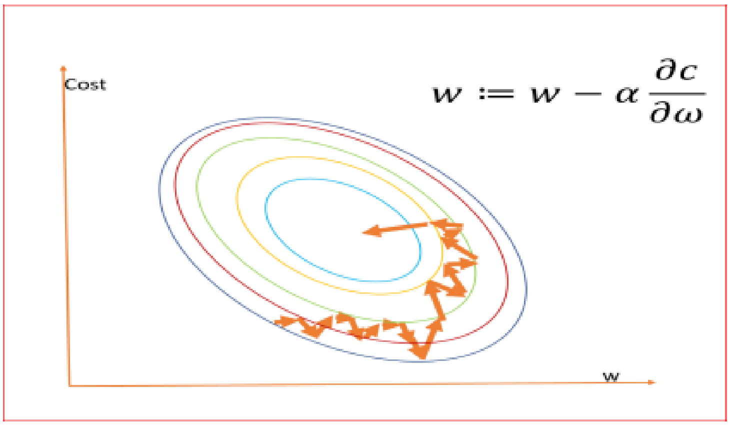


Figure 4.17: SGD optimizer

A sample having a randomized value aids in reaching at a global minimum and also in avoiding getting trapped at a local minimum.

The rate of learning becomes increased and also convergence becomes fast for huge datasets.

Advantages of stochastic gradient descent

- Rate of learning becomes efficiently increased in comparison with batch gradient.
- Redundancy is eradicated whenever a training sample is taken for calculation.
- In new datasets, weights may be renewed when training sets are taken for computation.

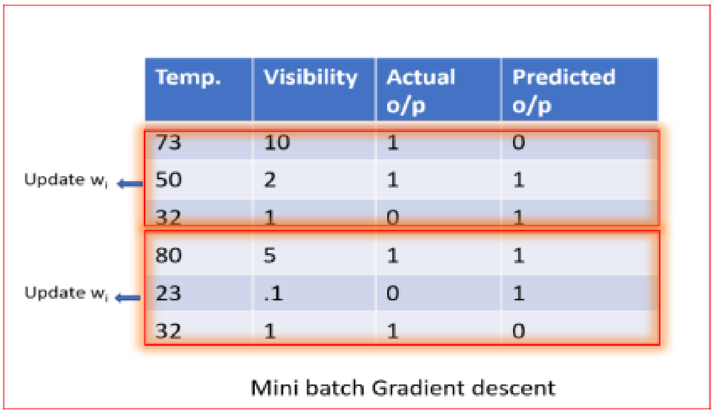
Disadvantages of stochastic gradient descent

- The value of Cost function keeps changing whenever we update weights.

Mini batch gradient descent

Mini batch gradient descent is a revised version of stochastic gradient descent. Unlike updating model parameters with just one training example, mini batch gradient descent employs a smaller batch of samples. This approach strikes a balance between the stability of batch gradient descent and the efficiency of stochastic gradient descent. It offers more consistent updates compared to stochastic gradient descent and tends to converge more rapidly by handling multiple samples simultaneously. The number of samples in each mini batch, or the batch size, can change according on the features and size of the dataset, providing optimization flexibility.

As we make use of a batch with various examples, it lessens the noise and distortion which is change of the weight refreshes and that assists with having a progressively quicker convergence.



Temp.	Visibility	Actual o/p	Predicted o/p
73	10	1	0
50	2	1	1
32	1	0	1
80	5	1	1
23	.1	0	1
32	1	1	0

Figure 4.18: Mini batch gradient table

Advantages of mini batch gradient descent

- Decreases the parameter's fluctuation and also causes to stability converge.
- The learning rate becomes quicker.
- Helps in calculating and locating the actual minimum.

Disadvantages of mini batch gradient descent

- For each mini batch loss is calculated and also this loss gets occupied across these batches.

4.14 Role of an optimizer

The function of an optimizer is to update factors of weight in order to reduce the value of loss function. Loss function informs the optimizer about its path. It tell us that which path is correct to touch the global minimum and which track is not.

Momentum

The first type is momentum. This type can be compared with a ball spinning down a hill. This ball attains momentum as it moves down.

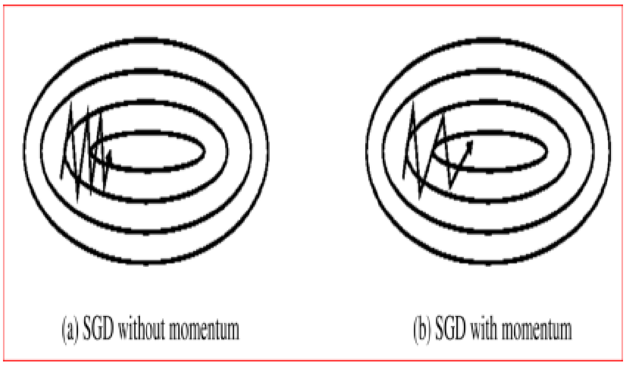


Figure 4.19: SGD with and without momentum

Momentum also supports the acceleration of gradient descent (GD), making it quicker when its curve been surfaced more sharply in one track than in another.

In order to make the weights updated, it makes use of the gradient of the existing step and also of the gradient of the preceding time steps. By doing this, convergence is approached faster.

By applying momentum optimizer, convergence is reached quicker.

$$V_t = \gamma V_{t-1} + \eta \nabla J(\theta; x, y) \tag{4.14.1}$$

$$\theta = \theta - V_t \tag{4.14.2}$$

Nesterov accelerated gradient

The next is nesterov accelerated gradient (NAG) optimization. This optimization can be compared with a ball which is rolling down the hill but now this ball is aware of its actions i.e. when it should slow down and when it should speed up.

Here the gradient is computed with respect to the coming step or the future step instead of the existing step. In this the gradient is estimated on the basis of look ahead and then the weights are updated.

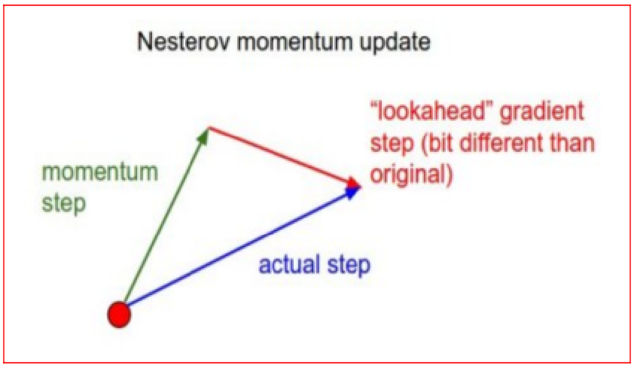


Figure 4.20: NAG movement

NAG can be explained by comparing it with a downward movement across a hill where only the front view is focused and not the back view i.e. only the future is seen. In this method, the descent is optimized quicker. This has a better performance than standard Momentum.

$$V_t = \gamma v(t-1) + \eta \nabla J(\theta - \gamma V_{t-1}) \tag{4.14.3}$$

$$\theta = \theta - V_t \tag{4.14.4}$$

Adam — Adaptive moment estimation (used Optimizer)

- One more strategy that figures the rate of adaptive learning individually of every factor present in the calculations of 1st and 2nd points of the incline.
- This is capable of decreasing drastically decreasing the rates of learning of Adagrad.
- Adam can be seen as a blend of Adagrad, which functions admirably on lighter gradientts and also of RMSProp which functions admirably in on the web and moving surroundings.

- Adam actualizes the exponential kinetic normal of the incline so that it can tune the learning rate rather than a straightforward normal as in case of Adagrad. Also, here there is a series of exponentially decreasing normal of the previous gradients.

- It works with efficiency. Also, it requires less storage.

- It among the most famous gradient descent optimization algorithms.

The Adam algorithm operates by first updating the exponential moving averages of the gradient (mgt) and the squared gradient (vgt), allowing it to estimate the first and second moments.

Hyper¬parameters betaA, betaB belongs to [0, 1) function by controlling the rates of exponential decay of the kinetic averages depicted as follows[36]:

$$MG(t) = \beta(A)mg(t-1) + (1-\beta(A))g(t) \tag{4.14.5}$$

$$VG(t) = \beta(B)vg(t-1) + (1-\beta(B))g(t^2) \tag{4.14.6}$$

Here MGt and VGt refer to the estimates of first and second moment respectively.

4.15 Recurrent neural network

RNN is a variety of neural network designed for sequence data processing. It is particularly useful for time series data analysis, as it can capture temporal dependencies. In the context of fault detection for inverter time series datasets, RNNs can be employed to learn patterns and anomalies in the data over time.

How it works for fault detection

- RNNs process sequences by maintaining a hidden state that changes with each time step. This hidden state retains information from prior time steps; hence, it models time dependencies.

- An RNN can be trained on a historical dataset of inverter performance as seen in inverter fault detection. In such training, the network learns what patterns of operation are normal. Deviations from the learned patterns can be detected by new data upon application of the model, which signals potential faults.

RNN vs. LSTM (Long short-term memory)

RNN

- The standard RNNs have the problem of vanishing gradients, which may impede their learning of long-range dependencies within sequences.
- They do very badly with learning dependencies from long ranges and also tend to forget information from earlier time steps while processing later ones.

LSTM

- LSTMs belong to a certain class of RNN architecture that is designed in a special way to counteract the issues that arise due to the vanishing gradient problem.
- They have a more complex structure in the way that they contain specialized memory cells and gating mechanisms through which they can capture long-term dependencies within the data.
- LSTMs are equipped with longer and efficient memory cells for tasks with long sequences and have become the de facto way for many sequence-related problems, including time series analysis.

Bidirectional LSTM

A bidirectional LSTM is an extension of the conventional LSTM, with the ability to process the input sequence in both directions: forward and backward. The architecture finds wide applicability in problems related to NLP and sequence modeling.

How it works

- Bidirectional LSTMs have two sets of hidden states: one processes the sequence from the beginning (forward), and the other processes it from the end (backward).
- Dependencies are combined from both directions for every time step. The model can capture dependencies in data that depend on both past and future contexts.

- Bidirectional LSTMs are handy when contexts from both directions are vital to making accurate predictions or picking up anomalies. This is particularly useful in fault detection of time series data. With the future context also taken into consideration, it increases the model's ability to recognize abnormal patterns.

In summary, RNNs are suitable for time series data analysis, but LSTMs, especially those of the bidirectional type, are often preferred due to their ability to capture long-range dependencies and consider both past and future context. LSTMs and bidirectional LSTMs can be helpful in fault detection using inverter time series data.

4.16 Inception time model

Inception Time is a deep learning model for both time series forecasting and classification tasks. Drawing inspiration from the Inception architecture originally designed for image recognition, we adapt this architecture to the realm of time series data. Inception Time works on tasks that include fault detection from time series datasets, as these architectures have shown great promise in picking out complex temporal patterns and anomalies. Here is how Inception Time works:

Inception module

An inception module within the Inception Time architecture houses multiple convolutional filters for processing time series data with different kernel sizes. These filters capture patterns over different scales of time, thus giving the model an ability to learn both short- and long-term dependencies in data simultaneously.

Depthwise separable convolutions

This architecture reduces the number of parameters in the model. This not only makes the model more efficient but also helps avoid overfitting, especially in cases where you have limited data.

Bottleneck blocks

Inception Time uses bottleneck blocks exactly like the ones found in Inception architectures for images. These blocks are implementations of 1 x 1 convolutions in order to reduce the data dimensions before applying more operations that are computationally more intensive. This aids in capturing informative features efficiently.

Shortcut connections

An Inception Time network uses shortcut connections, which facilitate the flow of gradients during training. It is thus very crucial for effective training of deep neural networks and avoiding vanishing gradients.

Global average pooling

A common use of this is at the end of the network in Inception Time, whereby feature maps are grouped into a fixed-size representation, and then that representation is fed into the very last classification/regression step.

In other words, Inception Time is a deep learning model for time series data using inception modules, depthwise separable convolutions, bottleneck blocks, and shortcut connections to ensure the fast capture of relevant information in the temporal domain. Such characteristics, together with the flexibility, efficiency, and competitive performance, make the proposed approach very attractive for dealing with fault detection in inverter time series datasets and other time series analysis tasks.

4.17 1D-ResNet model

One-dimensional Residual Network (1D-ResNet) is the structure of deep learning proposed mainly for the processing of one-dimensional data, for example, time series data. It is an extension from the Residual Network (ResNet), which was initially proposed as an architecture for classifying images. The main idea of ResNet and 1D-ResNet is residual connections to train very deep networks without being affected by the vanishing gradient problem.

Here is how a 1D-ResNet model is applied to the fault detection of inverter time-series data.

Input data

Basically, the input to fault detection in one's inverter time series data is basically 1-D time series signals; these are measurements recorded over time, say voltage, current, or any other relevant parameter of an inverter.

Residual blocks

A 1D-ResNet is constructed with several such residual blocks, where each residual block has a stack of convolutional layers. This design is meant to capture different levels of temporal features in time series data.

Skip connections

One of the most important features shared by ResNet and 1D-ResNet is the skip connections, or shortcut connections. Skip connections, in other words shortcuts, are connecting the input with the output of a residual block, thus adding that output to the original input, thus skipping one or many layers of the network. This architecture helps reduce the vanishing gradient problem when the networks are very deep. By preserving information from earlier layers and allowing gradients to flow more effectively during training, skip connections enable the successful training of deep neural networks with improved performance and convergence.

Batch normalization

Batch normalization is often used within each residual block to stabilize training and improve convergence.

Activation function

Typically, ReLU (Rectified Linear Unit) or other activation functions are used after convolutional layers to introduce non-linearity.

Global average pooling

Following the residual blocks, a global average pooling layer is employed to decrease the spatial dimensions of the data, creating a consistent-length feature vector encompassing the entire time series.

Fully connected layers

The global average-pooled feature vector is supplied into fully connected layers for the final classification or regression tasks related to fault detection.

Output layer

The output layer depends on the specific problem. For fault detection, it might be a binary classifier (normal or faulty) or a multi-class classifier (different types of faults).

4.18 Other parameters

Accuracy function in CNN

An accuracy function intends to measure the accuracy of a model. It gives us an estimate about the Algorithm's functions. It's tested after the model learns its parameters. Then test samples are analyzed and checked if errors are there with true dataset. This function tells us that how accurate and error free the model is by comparing the model's prediction with the original data. It's calculated in the form of percentage.

Loss function in CNN

In this function the loss of the model is measured. It gives us the information about the performance of the model that how well or poor the model is functioning after each iteration. The lower this loss value is, the Better the model behaves. It is a sum of the errors in the training sets. Its value is either negative or sum of squares. Its described as the original and forseen value difference. It optimizes the built model.

Epoch

One epoch in the context of training a neural network refers to the process of forwarding the entire dataset through the network once and then backward through the network for parameter updates using techniques like gradient descent. It signifies a complete cycle of training data being utilized to update the network's parameters once.

An epoch in the context of artificial neural networks represents a whole cycle of the training dataset. Neural networks are typically trained throughout several epochs. Essentially, we expect improved generalization when a neural network is exposed to fresh, "unseen" input (test data) after it has been trained on training data in a variety of configurations and styles for multiple epochs. An epoch is commonly associated with an iteration.

One epoch can also lead to under fitting of the curve as shown below in the graph:

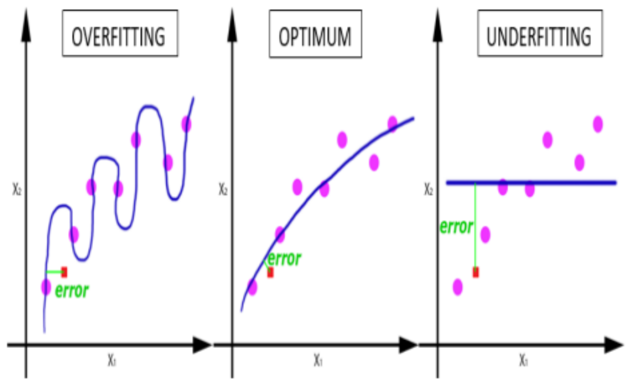


Figure 4.21: Model fitting curves

Iteration

Iterations is the quantity of batches or ladders through divided packets of the training data, needed to finish one epoch.

To get the iterations you just need to know calculations. Iterations is the quantity of batches required to finish one epoch. The batches number and the iterations number is kept the same for a single epoch.. For instance, there are 2000 training examples that need to be utilized. We deal with this example by dividing the dataset consisting of 2000 examples into a number of 500 batches. Then 4 iterations will be taken to accomplish a single epoch.

Validation data

It is a collection of data intended to train artificial intelligence with the purpose of building a desired model. It differs from training sets as it is an intermediate phase for selecting the best model. After measuring the loss, it evaluates the model Periodically. Based on these evaluation results the model will do its tuning and improvise its parameters.

Verbose in CNN

Verbose is an option available in many soft wares which provides further details about the computer that what the computer is performing and what is loading in it. By adjusting its value between 0,1,2 we can check the progress of each epoch.

If verbose = 0, nothing will be displayed on screen.

If verbose = 1, animation will be shown on screen.

Dataset

Dataset is a collection of samples on which model is trained. Here for our project we use voltage signal dataset. As we trained our model on google Colab so, we load our dataset on google drive. Then we trained our model on Colab by indicating the dataset path in google drive.

CHAPTER 5

Results & Discussion

The testing procedure of the CNN-1D model on the testing dataset involves several steps to evaluate its performance in fault detection for the open-switch cascaded H-Bridge 5-level inverter. Initially, the preprocessed testing dataset, consisting of segmented time-domain voltage waveforms, is fed into the trained CNN-1D model. The model then processes the input data through its layers, including convolutional, pooling, and fully connected layers, to extract and classify features related to different fault types. Since the task is classification, the model's output layer employs the softmax activation function to predict the types of faults for each input waveform segment.

After obtaining the predictions from the model, the predicted fault types are compared with the actual fault types in the testing dataset to calculate the accuracy of the model. Accuracy is calculated by dividing the number of correctly predicted fault types by the total number of testing samples, then multiplying by 100 to present it as a percentage.

In the section, the study finding of CNN -1D model that was developed for dealing with fault detection in open switch cascaded H-Bridge 5-level inverter are presented. First, author present the evaluation values that will be used to evaluate the proposed CNN-1D algorithm. The accuracy of the model achieve by this model is 98.7% and loss of the model is 0.17%.

After that, the results of CNN model training and testing are presented in Fig. 5.1 and 5.2 respectively which include the findings of model accuracy, and model loss function curves on 20 learning epochs for the proposed deep learning model. This model is trained using Adam optimizer, which achieves better results as compared to other optimizer.

The test case when switch 1 and 3 are faulty at a time, then the results of performance metrics results is this scenario are shown in Fig. 5.3 and calculated values are shown in table 5.1.

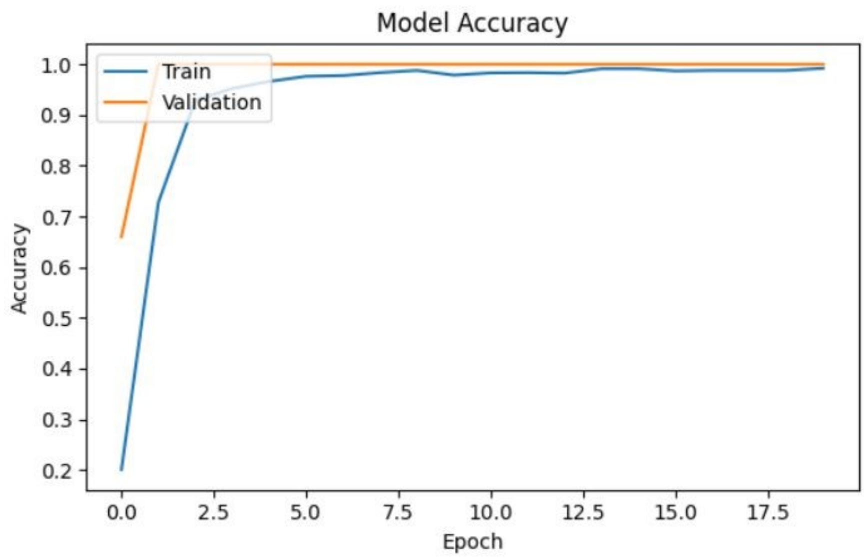


Figure 5.1: CNN-1D model accuracy vs epoches

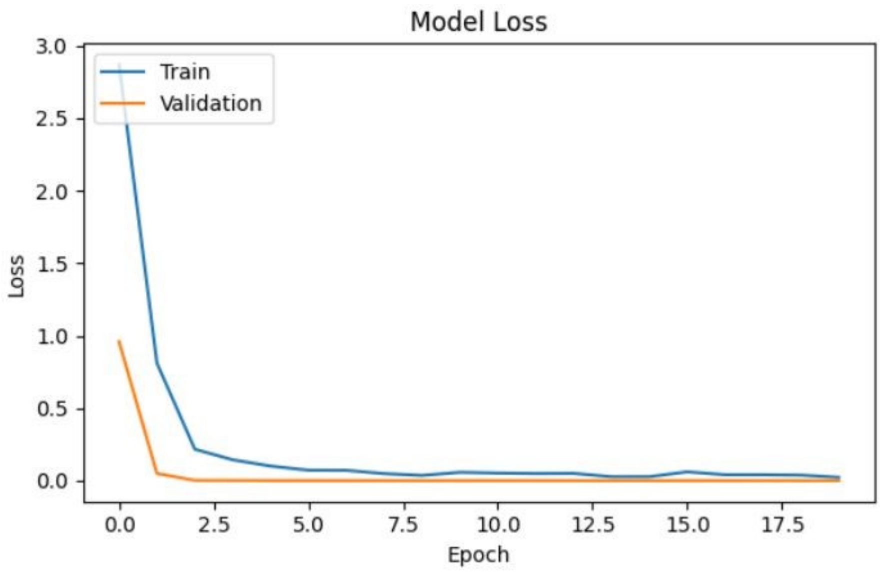


Figure 5.2: CNN-1D model loss vs epoches

The Performance metrics are measures used to assess the effectiveness, efficiency, and overall success of a system, process, or activity, here performance metrics for specific case is shared in Fig. 5.3.

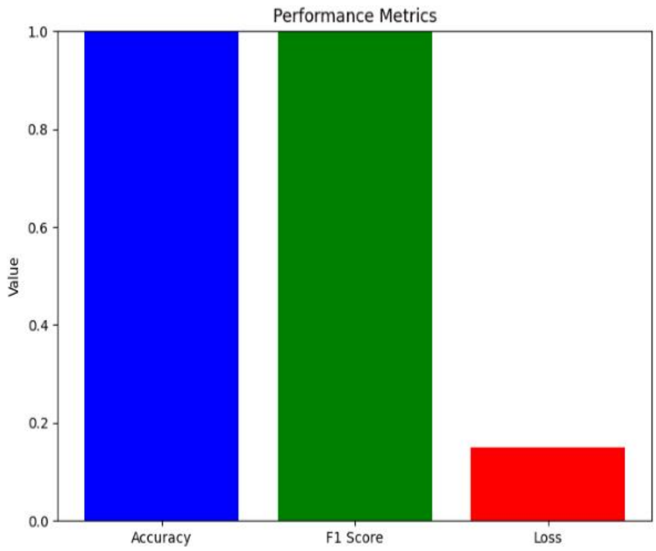


Figure 5.3: Performance metrics for switch 1 & 3 faulty

Table 5.1: Performance metrics for switches faulty 1 & 3

S. No	Metric	Value
0	Accuracy	1.000000
1	F1 Score	1.000000
2	Loss	0.177573

For the comparison purpose, the author trained models using different deep learning techniques, RNNs are designed to process sequential data by maintaining internal memory. A common variant, particularly for sequence classification tasks, is the Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) architecture due to their ability to capture long-range dependencies. For this paper we used 3 numbers of LSTM layers to capture varying levels of abstraction. The number of hidden units in each LSTM layer can be adjusted based on the complexity of the dataset and computational resources. For training of model, author used the sigmod activation function. The learning rate can be determined through experimentation, and first time get common values from literature which is 0.01, in Fig. 5.8 and Fig. 5.9 demonstrate the model accuracy and model loss respectively for RNN based model on 20 learning epochs with help of Adam optimizer. As shown in Fig. 5.8 & 5.9, author can observe that model accuracy is round about 89% only, the main reason behind is that, RNN used the LSTM method, so for this specific generated dataset, RNN model does not gives as good accuracy as CNN-1D gives.

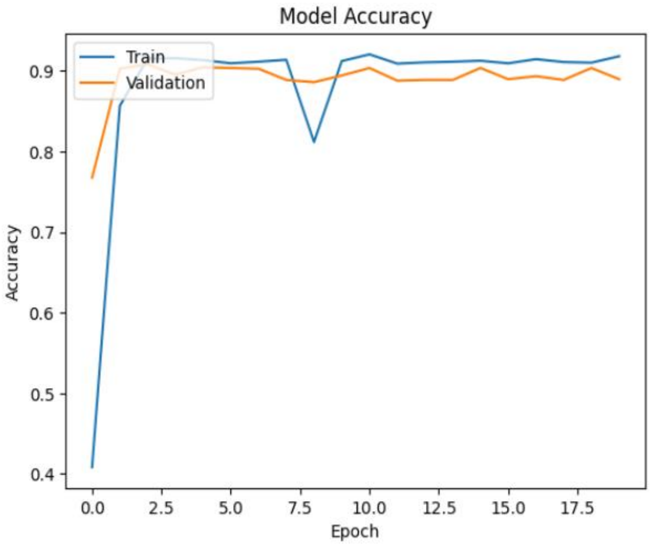


Figure 5.4: RNN model accuracy vs epoches

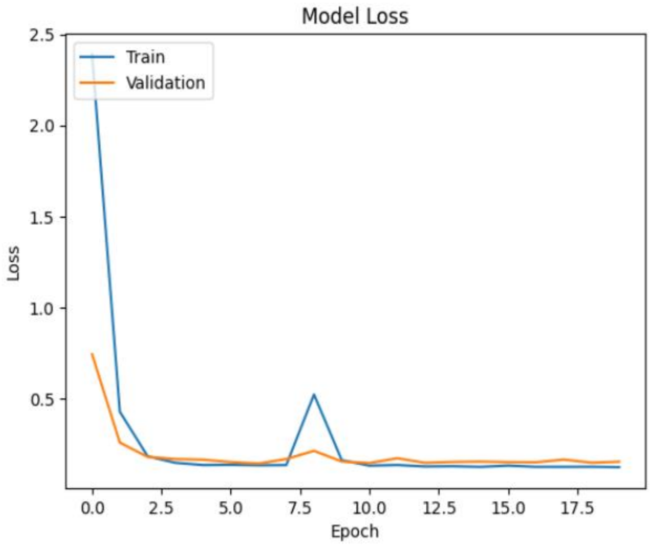


Figure 5.5: RNN model loss vs epoches

Fig 5.6 and Fig 5.7 demonstrate the model accuracy and model loss respectively for Inception time-based model on 20 learning epochs with help of Adam optimizer. Time inception models are sensitive to the distribution of the training data. If the distribution of the test data differs significantly from the training data, performance may degrade will CNN-1D model does not suffer with this problem.

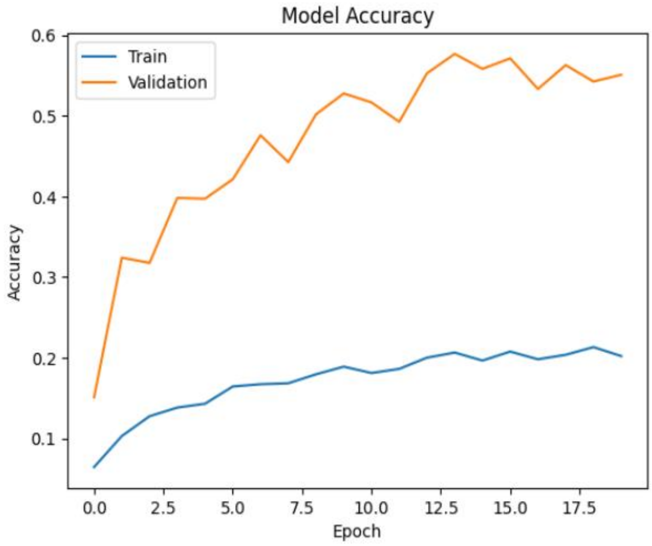


Figure 5.6: Time inception model accuracy vs epoches

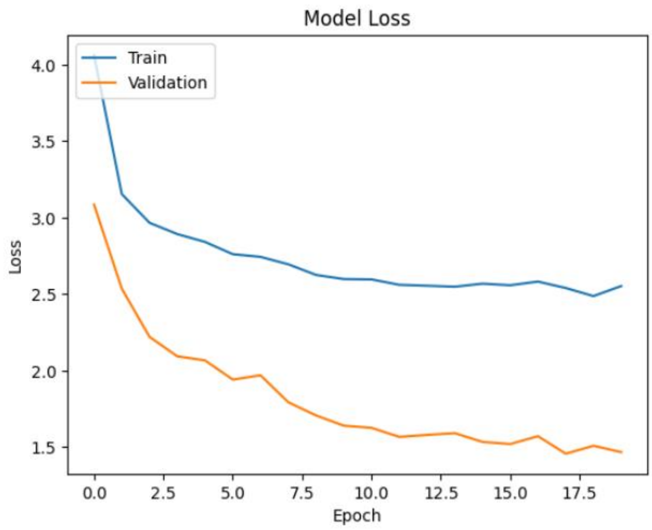


Figure 5.7: Time inception model loss vs epoches

ResNet is defined by its residual blocks, which facilitate the training of extremely deep networks by addressing the vanishing gradient issue. Typically, ResNet comprises multiple stacked residual blocks. The depth of the network can vary, determining the number of blocks and layers within each block. Each residual block comprises convolutional layers, followed by shortcut connections. Here we experiment with different configurations of convolutional layers and the number of filters in each layer. But the final ResNet model contain 4 residual blocks for model training for the generated dataset. ReLU is used as the activation function within each residual block. Batch normalization technique applied before the activation function to improve training stability. Fig 5.8 and Fig 5.9 demonstrate the model accuracy and model loss respectively for 1D-Resnet based model on 20 learning epochs with help of SGD optimizer, the issue with this model for the generated dataset is that with a large number of layers, are prone to overfitting, particularly when the training dataset is limited. Overfitting can result in poor generalization to new, unseen data.

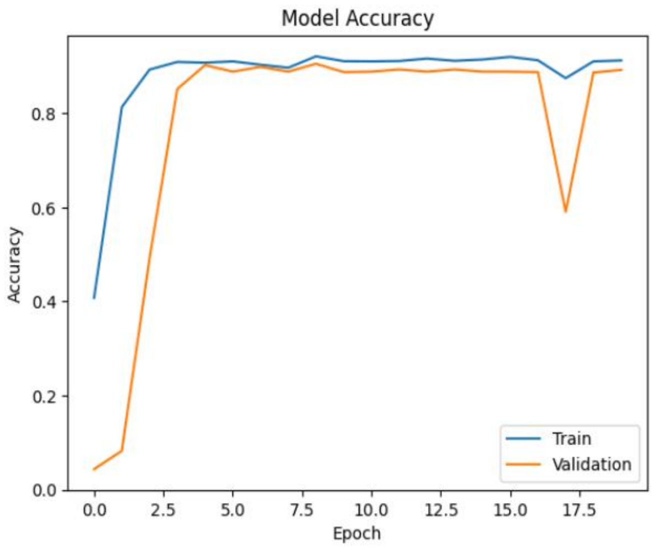


Figure 5.8: 1D-Resnet model accuracy vs epoches

For this thesis different deep learning models are trained on the collected dataset of cascaded H-Bridge 5 level inverter for making comparisons between these models with CNN-1D model. The Table5.2 below shows the comparison based on accuracy, F-score, and loss. This was done for simplicity of reader for better understanding why we pick CNN-1D over other models.

Evaluation metrics such as accuracy, precision, recall, and F1-score gauge the CNN-1D's performance in distinguishing normal from faulty conditions. This approach demonstrates the potency of CNN-1D architecture in advancing fault diagnosis and classification for dynamic systems like

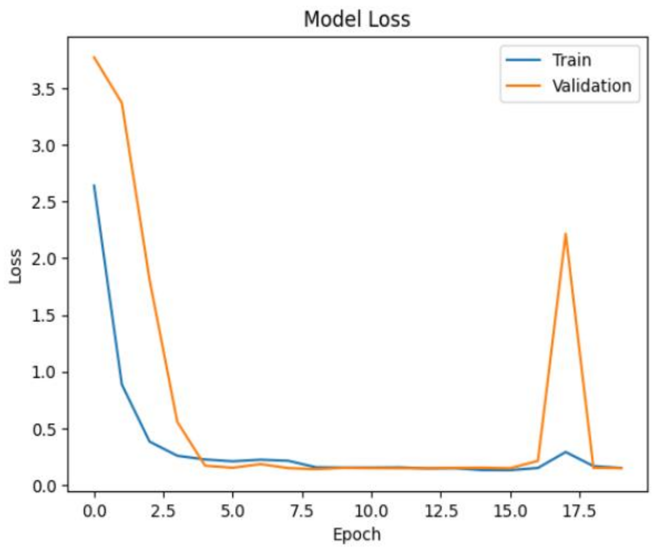


Figure 5.9: 1D-Resnet model loss vs epoches

the CHB MLI over other deep learning models.

Table 5.2: Comparision of different deep learning models

S. No	Trained Model	Test Accuracy	Loss
1	CNN-1D	0.9879	0.0379
2	RNN	0.8898	0.1648
3	Inception Time	0.8944	0.1787
4	Hybrid Architectures	0.0231	Nan
5	1D ResNet	0.8888	0.1452

In summary, the proposed fault diagnosis approach includes dataset preparation, CNN architecture, and training and testing procedures. The approach is designed to detect open switch faults in CHB-5LIs using voltage measurements only and can also detect maximum two faults at the same time. The proposed approach can achieve high accuracy, precision, recall, and F1-score for fault diagnosis in CHB-5LIs.

CHAPTER 6

Conclusion

In conclusion, the application of deep learning, specifically the CNN-1D model, has demonstrated promising capabilities in fault diagnosis for the cascaded H-bridge 5-level inverter (CHB-5LI). Our proposed approach exhibited a high accuracy rate of 98.7% in fault detection, highlighting its superior performance compared to traditional fault diagnosis methods. Specifically, RNN achieves 88.9 percent accuracy, 1D-ResNet achieves 88.8 percent, and the Time Inception model achieves 89.4 percent accuracy on the same dataset. The CNN-1D model not only accurately diagnosed faults but also detected multiple faults simultaneously, a significant advancement that enhances the efficiency and reliability of fault diagnosis systems. Moreover, our CNN-1D method exhibits a faster fault diagnosis time of 0.060 ms compared to 0.062 ms for RNN and 0.065 ms for ResNet. These findings highlight the potential of deep learning techniques to revolutionize fault diagnosis in intricate power electronics systems.

Furthermore, the robustness of our proposed approach was evident as it showcased less sensitivity to variations in operating conditions and different fault types. This resilience is crucial for practical applications where the inverter may operate under diverse conditions, ensuring consistent and reliable fault detection performance. The reduced sensitivity to varying conditions makes our approach more adaptable and versatile, catering to the dynamic operational environments typically encountered in real-world applications of CHB-5LI systems.

Lastly, the accessibility and ease of implementation of our proposed CNN-1D based approach are notable advantages, requiring less expert knowledge compared to traditional fault diagnosis methods. This accessibility lowers the entry barrier for practitioners and engineers in the field, facilitating the adoption of advanced fault detection techniques for CHB-5LI systems. Overall, our study demonstrates that leveraging deep learning techniques like CNN-1D can significantly enhance fault detection capabilities in CHB-5LI systems, paving the way for more efficient, reliable, and accessible fault diagnosis solutions in the field of power electronics.

6.1 Future research

We aim to complement our simulation-based approach with experimental validation to enhance the reliability and applicability of our fault diagnosis method for CHB-5LIs. Specifically, we recognize the need to investigate the impact of saturation and dead time effects, which can potentially exist in practical implementations of CHB-5LIs. Saturation effects may occur due to limitations in the magnetic components or power semiconductor devices, leading to non-linear behavior in the inverter's operation. On the other hand, dead time is a period during which both switches of an H-bridge inverter are turned off to avoid the appearance of shoot-through currents. It is important to know their detrimental effects on the performance of the inverter system since this may add even more complication and uncertainty and thus impact the accuracy of fault diagnosis. Therefore, in future investigations, we will delve into saturation and dead-time effects on voltage waveforms and the implications for fault diagnosis. This is going to be by performing experimental studies of real-world phenomena, hence validating results obtained by simulation. With the above considerations, our work ultimately aims toward more comprehensive and robust development in fault diagnosis of CHB-5LIs while accommodating practical challenges during implementation.

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