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Submitted by: AD Hana & SERKOU Arwa Oum elbaha

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Fault diagnosis of power electronic converter

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Deform the Jury :

Mr. ACHBI Mohamed Said	*MCB at the University of Ouargla*	*President*
Mr. ROUABAH Boubakeur	*MCA at the University of Ouargla*	*Director of Memory*
Mr. Kafi Mohamed Redouane	*Prof at the University of Ouargla*	*Co-Director of Memory*
Mr.MAHBOUB Mohamed Abdelbasset	*MCA at the University of Ouargla*	*Examiner*

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Dedication

I dedicate this humble work to :

My dear mother the source of inspiration, positivity and continuous encouragement

To the spirit of my late father, Your unwavering love, wisdom, and support have been my guiding light, even in your absence.

to my dear brothers and sisters. Your unwavering support, encouragement, and love have been my source of strength throughout this journey.

To my friends, for their continuous encouragement and understanding.

To my mentors and professors, for their invaluable guidance and wisdom throughout this journey.

Thank you all for being my pillars of strength.

AD Hana

Dedication

To my dear parents, I dedicate this success to you for your learning and efforts.

You were the biggest supporter and constant motivator during my journey.

To my brothers, my support and those in whom I see the fruit of my success, to my family, each in his name, to myself who persevered and struggled.

SERKOU Arwa Oum elbaha

Remerceiment

Qt the end of our training cycle we would like to thank God the almighty our most sincere thanks go to Mr. ROUABAH Boubaker for their valuable advice and follow-up that he gave me throughout our work my sincere thanksgo to the jury members for agreeing to judge my present work. Finally , anyone who participated directly or indirectly in the completion of this dissertation sincerely thank you and the teachers who participated in our training be sincerely thanked .

AD Hana

SER KOU Arwa Oum elbaha

Abstract

Modular Multilevel Converter MMCs are an advanced power electronics topology that has many advantages, including high efficiency, scalability, and superior harmonic performance. However, as with any complex system, MMC devices are susceptible ti errors that can affect their operation and reliability. Machine learning is one of the most important technologies to enhance fault diagnosis in MMC, enabling rapid identification and remediation of problems to reliability of power conversion systems.

Key word: Modular Multilevel Converter, Machine learning, power conversion systems.

Résumé

Les convertisseurs multiniveaux modulaires (MMC) constituent une topologie électronique de puissance avancée qui présente de nombreux avantages, notamment un rendement élevé, une évolutivité et des performances harmoniques supérieures. Cependant, comme pour tout système complexe, les appareils MMC sont sensibles aux erreurs qui peuvent affecter leur fonctionnement et leur fiabilité. L'apprentissage automatique est l'une des technologies les plus importantes pour améliorer le diagnostic des pannes dans les MMC, permettant une identification et une résolution rapides des problèmes afin de garantir des performances et une fiabilité continues des systèmes de conversion de puissance.

Les mots clé : Les convertisseurs multiniveaux modulaires , L'apprentissage automatique , systèmes de conversion de puissance .

ملخص

المحولات المعيارية متعددة المستويات عبارة عن طوبولوجيا متطورة لإلكترونيات الطاقة تتمتع بالعديد من المزايا، بما في ذلك الكفاءة العالية وقابلية التوسع والأداء التوافقي الفائق. ومع ذلك، كما هو الحال مع أي نظام معقد، تكون أجهزة ةةؤ عرضة للأخطاء التي يمكن أن تؤثر على تشغيلها وموثوقيتها. يعد التعلم الآلي أحد أهم التقنيات لتعزيز تشخيص الأخطاء في ، مما يتيح التعرف السريع على المشكلات ومعالجتها لضمان استمرار الأداء و الموثوقية لأنظمة تحويل الطاقة .

الكلمات المفتاحية : المحولات المعيارية متعددة المستويات , التعلم الآلي, أنظمة تحويل الطاقة.

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ACRONYMS

AC	Alternating current
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
BM	Blocking Mode
CNPC	Cascaded neutral-point clamped
DC	Direct current
DT	Decision Tree
FB	Full-bridge
FC	Flying capacitor
FN	False Negative
FP	False Positive
HB	Half-bridge
HNPC	H-bridge neutral-point clamped
HV	High-voltage
HVAC	High-voltage alternating current
HVDC	High-voltage direct current
IGBT	Insulated-gate bipolar transistor
IGCT	Integrated gate-commutated thyristor

ACRONYMS AND SYMBOLS

MC	Matrix converter
ML	Machine Learning
MLCs	Multi-Level Converters
MMC	Modular multilevel converter
PWM	Pulse width modulation
SM	Submodule
SVM	Support Vector Machines
TN	True Negative
TP	True Positive
VSC	Voltage source converter

ACRONYMS AND SYMBOLS

SYMBOLS

Notation

P, Q, S	Active, reactive, and apparent power
R, L, C	Resistance, inductance, and capacitance
v, i, ψ	Voltage, current, and ux linkage (Peak values)
V , I, Ψ	Voltage, current, and ux linkage (RMS values)
x	Phase variable $\in \{a, b, c\}$
y	Arm variable $\in \{u, l\}$

General introduction

General introduction

In recent years, the utilization of power electronic converters has surged across various sectors, ranging from renewable energy systems to electric vehicles and industrial automation. These converters play a pivotal role in controlling the flow of electrical energy, converting it from one to another, and facilitating efficient power distribution. However, with the increasing complexityand criticality of these systems, the need for effective fault diagnosis methods has become paramount.

Traditional fault diagnosis approaches for power electronic converters often rely on rule-based systems or model-based techniques, which may struggle to accommodate the diverse and dynamic nature of faults in real-world scenarios. As a result, there is a growing interest in leveraging machine learning (ML) classification algorithms for fault diagnosis in power electronic converters.

ML classification techniques offer a data-driven approach to fault detection and diagnosis, capable of learning complex patterns and relationships from large datasets of historical operational data and fault signatures. By employing algorithms such as decision trees, support vector machines, random forests, or neural networks, ML-based fault diagnosis systems can accurately identify and classify various types of faults in power electronic converters.

In references[1-3] a machine learning approach used for multilevel converter in renewableenergy,

The purpose of our work is exploring the application of ML classification in fault diagnosis of modular multilevel converter (MMC). Throughout this memoir we will delve into the principles of ML classification, examine the challenges and opportunities specific to fault diagnosis in power electronic systems, and investigate the performance and effectiveness of different ML algorithms in detecting and classifying faults. Additionally, we will explore the implications of integrating ML-based fault diagnosis systems into practical applications, aiming to enhance reliability, mitigate downtime, and optimize maintenance strategies in power electronic convertersystems.

This dissertation is organized as follow:

In chapter one, we gave general information on the Power Converter and the Multi-level Converter. Then, in chapter two, machine learning classification methods are presented. Next, in the third chapter, simulation results, analysis, and discussion of modular multilevel converter are detailed. Finally a conclusion section summarizes the findings of our work

Chapter I

Power electronic converters

Chapter I: Power electronic converters

I. Power electronic converters

I.1. Introduction

Power electronics applies solid-state electronics to regulate and transform electrical power from one form to another, including converting between AC and DC, adjusting voltage and current levels, altering frequency, or combining these functions. Power electronic converters find widespread use across a broad spectrum of power conversion tasks, spanning from low-voltage, low-power applications to high-voltage, high-power scenarios. In certain instances, multiple converters may be interconnected in series, parallel, or cascade configurations to achieve multistage power conversion. While specific applications vary, the overarching objectives typically revolve around five key factors: energy efficiency, power density, cost-effectiveness, system complexity, and reliability. These aspects are interconnected, with each influencing the others to varying degrees.

I.2. Type of power converter

The power converter has four types, since each one plays a crucial role in the proper functioning of our electronic devices and our systems. They play an essential role in the machine that is our increasingly electrified world, mention it:

I.2.1. AC to DC converter(Rectifies)

AC-DC converter, also called rectifiers, are used to transform alternating current AC into direct current DC. These converters are usually found in power supplies for electronic devices such as laptops, televisions and phone chargers.

I.2.2. DC to AC converter (Inverter)

A DC-AC converter, commonly known as inverter, perform the reverse function of rectifiers. They turn the DC into AC. Inverter are commonly used in renewable energy systems such as solar panels, which produce dielectric electrical power that must be converted into currentelectrical power to be used in household appliances .

I.2.3. DC to DC converter (Chopper)

A DC-DC converter are used to modify the voltage level of a DC power source. They play an essential role in mobile devices and computers where different components require different voltage levels; for example, the processor of a laptop and LED panel may require different voltages, which is facilitated by a DC-DC converter.

I.2.4. AC to AC converter (Cycloconverter)

AC-AC converter are devices that transform one form of AC into another, usually by changing the magnitude of the current and frequency. Their use is frequent in motor speed controlapplications, such as variable air conditioning or changing stations for electric vehicles.

I.3. Two-Level power converter

I.3.1. Definition

A two-level power converter (Figure I.1) is a type of power converter that typically provides two voltage levels at its output. It can be designed using various models, such as switching function (without using rectifier mode), average model (controlled by U_{ref}), or average model (without U_{ref} control).Such converters are frequently employed in a number of applications, including renewable energy.

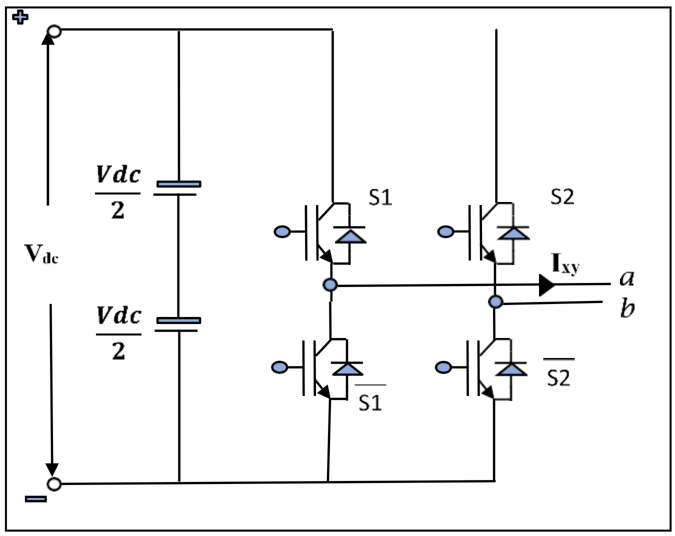

Figure I.1Two-Level power converter configuration

A two-level power converter works by converting direct current (DC) to alternating current (AC) by switching the output voltage between two levels. Here is a brief explanation of its operation:

- It consists of six electronic switches (such as IGBTs or MOSFETs) arranged in a three-phase bridge configuration.
- The switches control the conversion of the DC voltage between two levels: +Vdc and -Vdc.
- Pulse Width Modulation (PWM) techniques are used to rapidly switch the switches on and off, controlling the shape and frequency of the output.

- The converter produces a square wave or a modulated wave that can be filtered to convert it into a sinusoidal wave.

I.3.2. Advantages of Two-Level power converter

- Dependability and Simplicity: The two-level converter topology is a popular and simple design found in many industrial applications.

Because of its great reliability and simplicity, it is a popular option for a variety of systems.

- Great Efficiency: Because power semiconductor switches lose very little power, two-level converters have great efficiency.

Their dependability and longevity are further increased by the lack of moving parts1.

- Cost-Effectiveness: Two-level converters are inexpensive to develop and implement.

Lower manufacturing costs are partly attributable to fewer components and simpler control systems.

- Harmonic Performance: Two-level converters are nevertheless appropriate for a wide range of applications, despite certain harmonic performance issues.

I.3.3. Disadvantages of Two-Level power converter

- A two-level power converter's significant harmonic distortion leads to poor power quality, which is a drawback.
- Two-level converters have difficulties with greater harmonic distortion levels, which affects the quality of the power output, in contrast to more sophisticated multilevel converters that can eliminate low-order harmonics.
- This restriction may result in problems like power transfer inefficiencies and interference with other electronic devices.

I.4. Multi-Level power converter

I.4.1. Definition

A multi-level power converter is a complex power converter that generates high voltage waveforms from low voltage components. These converters have been developed for over a century. Its origins date back to the 1880s, when the advantages of long-distance direct current transmission were recognized. Multilevel converters offer the advantages of improved power quality, efficiency, and the ability to eliminate low-order harmonics from the output waveform. They utilize advanced topologies and modulation strategies to improve their performance in high voltage and high power applications.

I.4.2. Types of Multi-level power converter

Three types of multi-level converters have been proposed: the diode-clamped inverter, the flying-capacitor converter in common DC sources, and the cascade converter in Isolated DC sources:

I.4.2.1. The diode-clamped multilevel converter

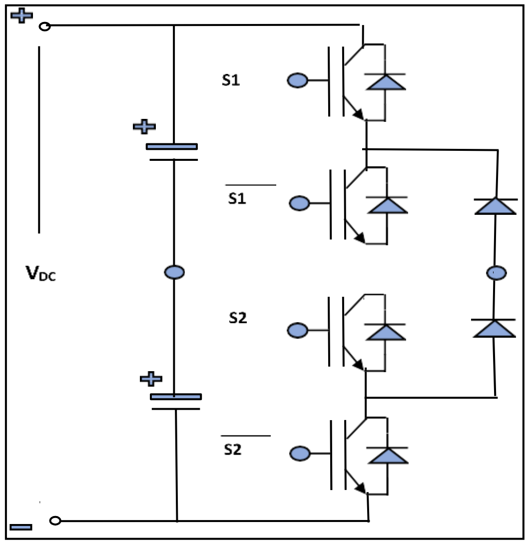

Figure I.2 :Three level diode clamped multilevel inverter

The diode-clamped converter as shown in figure I.2 is a type of multilevel converter topology that utilizes diodes to limit voltage stress on power devices, achieving steps in the output voltage. This inverter topology is commonly used in high-power applications due to its ability to provide multiple voltage levels through the connection of phases to a series of capacitors. The diode-clamped inverter is known for its straightforward operation and well-known structure, making it a popular choice in industry applications for medium to high-voltage power conversion needs.

I.4.2.2. The flying-capacitors multilevel inverter

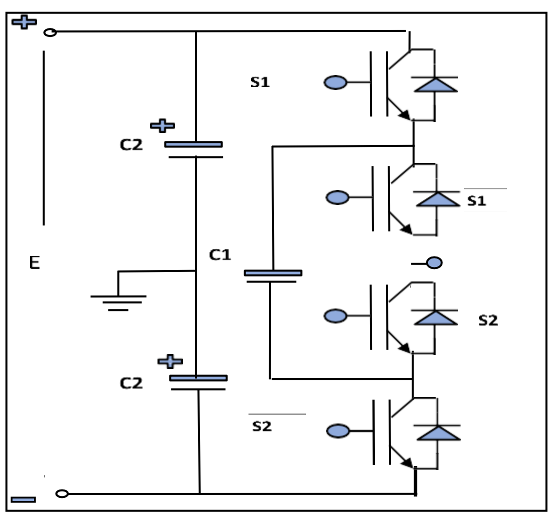

Figure I.3:Three level flying-capacitor multilevel inverter

A flying capacitor inverter (*figure I.3*) is a multi-level inverter that uses flying capacitors to store and transfer energy between different levels of the inverter [5-8]. These capacitors are connected in series and parallel to obtain the desired voltage level, making them important components in multilevel inverters used in various applications such as electric vehicles (EV), battery management systems (BMS), and renewable energy systems. Flying capacitors play a vital role in balancing voltage levels, reducing harmonic distortion in voltage waveforms and improving system power quality. They are particularly useful in applications where voltage equalization, energy storage and power quality optimization are important requirements.

I.4.2.3. The cascaded H-Bridge multilevel inverter

A cascaded H-Bridge multilevel converter (figure I.4) is a type of power converter that consists of multiple converter stages connected in series to achieve the desired output voltage or current levels. These converters offer advantages such as modularity, scalability, and improved power quality. They are commonly used in high-power applications where the conversion of voltage or current to specific levels is required.

The research and development in the field of cascaded converters have led to the proposal of innovative designs like the Interconnected Cascaded Converter (ICC), which aims to generate sinusoidal waveforms efficiently. Cascaded converters can be designed with various topologies, such as boost converters, buck converters, and hybrid configurations, to meet specific application requirements.

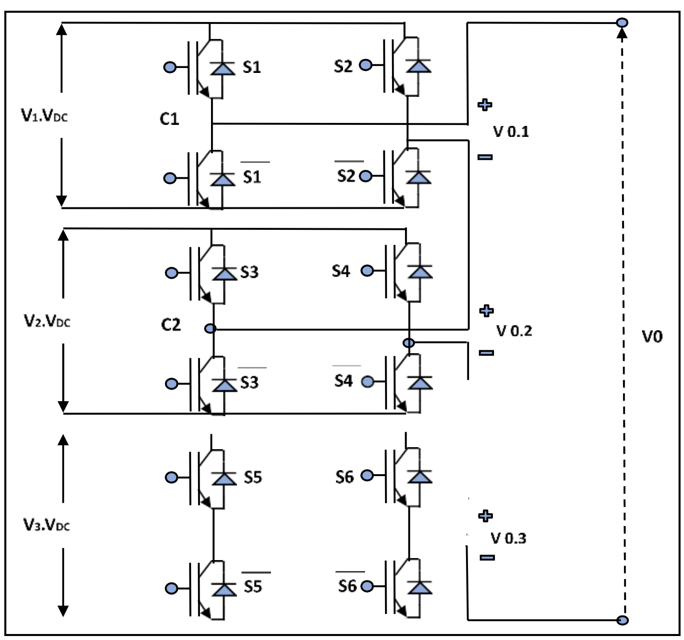

Figure I. 4: cascaded H-Bridge multilevel converter

I.4.3. Advantages of multi-level power converter

The advantages of multi-level power converter include:

- Improved power quality, Higher efficiency, Reduced harmonic distortion.
- The ability to achieve higher voltage levels with fewer components compared to traditional two-level converters.
- It offers enhanced performance in high-power applications, making them valuable for various industries and applications.
- It can operate at both fundamental switching frequencies, providing flexibility and efficiency in power conversion processes.

I.4.4. Disadvantages of multi-level power converter

Disadvantages of multi-level power converters include:

- Circuit design complexity,
- The need for additional gate driver circuitry for each added active semiconductor,
- The need for isolated voltage sources to form small voltage stages.
- It also face challenges related to voltage imbalance issues, voltage limiting requirements, and the limitations of achieving a large number of voltage levels due to these limitations.
- An increase in the number of active switches in a multilevel converter leads to higher costs and increased complexity in the overall system design.

I.5. Modular Multi-level Converter (MMC)

A modular multilevel converter (MMC) is utilized in high-voltage direct current (HVDC) transmission systems and other applications necessitating high-voltage conversion. Comprising numerous power electronic modules interconnected in series, it elevates voltage levels while minimizing harmonic distortion and enhancing efficiency. Through dynamic voltage adjustment across each module, the converter regulates output voltage precisely, facilitating precise voltage control and management of reactive power. Notable advantages of MMCs include scalability, fault tolerance, and modularity, rendering them well-suited for diverse power transmission and distribution scenarios.

I.5.1. Overview of Converter Topologies

I.5.1.1. Basic Principles

The Modular Multilevel Converter (MMC) operates based on several fundamental principles. Let's explore them:

1. Cell-Based Structure:
   - The MMC comprises multiple power cells connected in series to generate a medium voltage output.
   - Each phase includes two arms, each equipped with arm inductors.

- Power cells can be either "single submodules" (two IGBTs and one capacitor bank) or "double submodules" (four IGBTs and two capacitor banks).

2. Voltage Levels:

The MMC functions at two voltage levels: positive Vdc and negative Vdc.

It provides scalable, motor-friendly voltage and produces a virtually sinusoidal output current suitable for loads and motors.

I.5.1.2. Modular Multilevel Converters Configurations

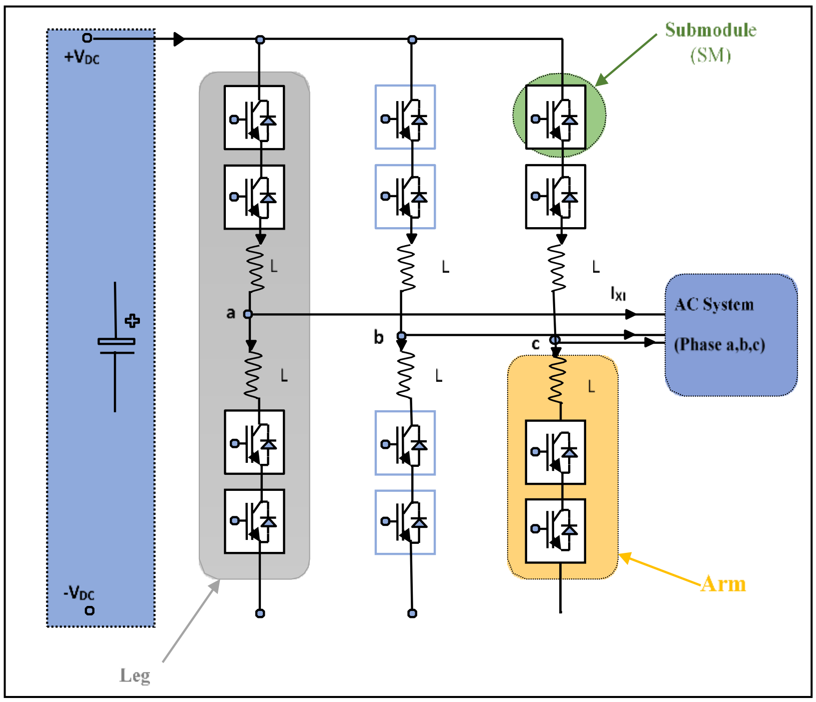

Figure I.5: Configuration of modular multilevel converter

The Modular Multilevel Converter (MMC) can be configured in various ways to suit different applications and requirements. The primary configurations include single-phase and three-phase setups, where each phase consists of two arms filled with multiple submodules. These submodules can be arranged symmetrically or asymmetrically, depending on the desired voltage levels and fault management needs. Additionally, cascaded MMCs connect multiple MMC units in series for handling higher voltage levels, and hybrid MMCs combine traditional MMCs with other converter topologies for enhanced performance. This modular and flexible design makes MMCs suitable for a wide range of applications, from high-voltage direct current (HVDC) transmission to renewable energy integration and large motor drives. A simplified general diagram of an MMC is illustrated in Figure I.5 By using many levels - that is, many more voltagelevels than a two- or three-level converter - an MMC can create a high-quality output voltage waveform with very low harmonic distortion.

I.5.1.3. Sub-Module Configurations

Sub-modules are the building blocks of MMCs. They form the converter arms and phase-legs. Each sub-module consists of a set of power semiconductor devices (such as IGBTs or MOSFETs) 1200–1700V and passive components (such as capacitors and inductors).The commonly used submodule configurations in a modular multilevel converter are:

- Half-bridge (HB) submodule

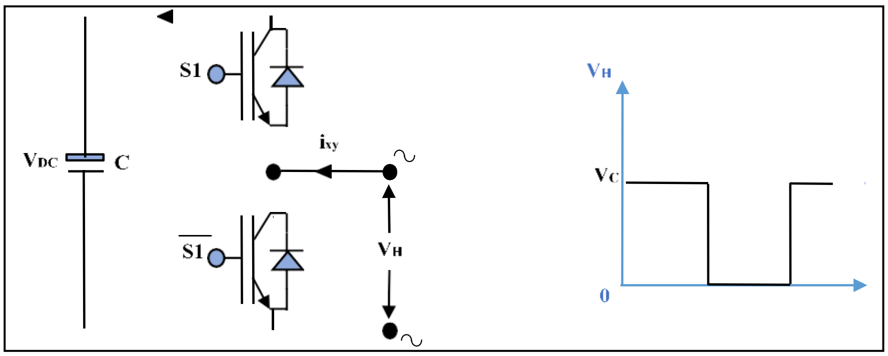

Figure I.6:Half-bridge sub-module and output voltage waveform

Half-Bridge Sub-modules (HB-SMs) are fundamental building blocks within MMCs.

Each HB-SM consists of a half-bridge configuration (Figure I.6). It is composed of two IGBT devices with anti-parallel diodes (S1 and $\bar{S}\bar{1}$) and one DC capacitor (C). The two IGBT devices are operated in a complementary manner to regulate the DC capacitor voltage at a value of V_C. The DC capacitor voltage is given by equation 1:

$$V_C = \frac{1}{C} \int i_C \, \partial t \qquad 1$$

The DC capacitor current in terms of AC current (i_{xy}) and the switching state of the top device S1 are given by:

$$i_C = S_1 i_{xy} \qquad 2$$

The DC capacitor current is equal to the AC current or zero, depending on the position of top switch S1.

Table I.1Switching states of HB SM

States	1	2	3	4
S_1	0	0	1	1
$\overline{S_1}$	0	1	0	1
V_H	-	0	$+V_{DC}$	-
Condition	Allowed			Distractive

As seen in Figure I.6, the half-bridge sub-modules AC output voltage has two voltage levels: "0" and " V_C." The AC output voltage is equal to V_C when the top switch is in the "ON" position. In this mode, the DC capacitor voltage rises when the current flows in a positive direction and falls when it flows in a negative direction. The AC output voltage is equal to "0" when the top switch is in the "OFF" position [2]. No matter which way the current flows, the DC capacitor voltage stays constant in this mode. The half-bridge submodule's AC output voltage can be expressed in terms of the DC capacitor voltage and the top device S_1 switching state as (equation3) :

$$V_H = S_1 V_C \qquad 3$$

- Full-bridge (FB) sub-module

H-bridge converter is another name for the full-bridge (FB) submodule. Figure I.7displays the full-bridge submodule's circuit configuration. It consists of one DC capacitor (C) and two half-bridge legs (S1, S1, and S2, S2). Two IGBT devices with antiparallel diodes make up each leg, and they are each run in a complementary way.

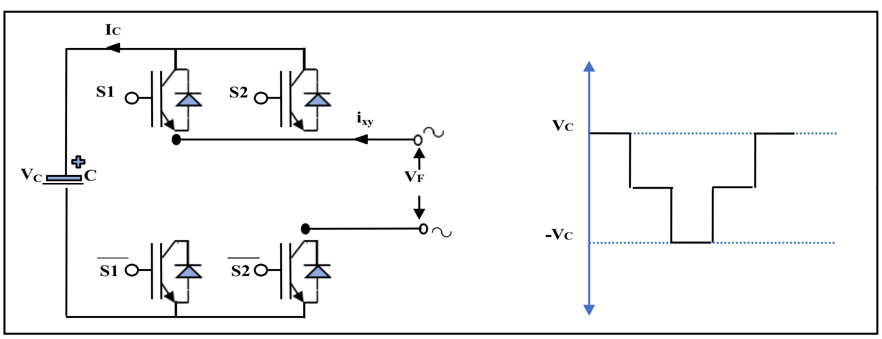

Figure I.7:Full-bridge (FB) submodule and output voltage waveform

The IGBT devices S1 and S2 are controlled in order to manage the DC capacitor voltage. Equation (2.1) gives the same formula for the DC capacitor voltage of the half-bridge submodule as it does for the full-bridge submodule. The condition of devices S1 and S2 determines the amount of current flowing through the DC capacitor. The current through a DC capacitor isgiven by equation 4:

$$I_C = (S_1S_2 - \bar{S}_1\bar{S}_2)i_{xy} \qquad 4$$

All possible combination of switching states for S1 and S2 are shown in Table I.2. The four switching combinations generate three voltage levels, “0,” “V_C ,” and “–V_C ”[2].

Table I.2:Switching states of FB SM

States	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
S_1	0	0	0	1	0	0	1	0	1
$\bar{S}_1$	0	1	0	0	1	1	0	0	0
S_2	0	0	1	1	1	0	0	0	0
$\bar{S}_2$	0	0	0	0	0	1	0	1	1
V_F	-	-	-	0	$-V_{DC}$	0	-	-	$+V_{DC}$
Condition	Allowed								

The full-bridge sub-module AC output voltage is displayed in Figure I.7. The AC output voltage is identical to "V_C" when IGBT devices S1, S2 are "ON." In this mode, the voltage of theDC capacitor rises in the positive direction of the current and falls in the negative direction. Inthe switching states of S1-"ON," S2-"OFF," and S1-"OFF," S2-"ON," the AC output voltage willbe "0." No matter which way the current flows, the DC capacitor voltage stays constant in this mode. The voltage level "0" is represented by the two switching states of the full-bridge submodule. We refer to the extra switching states that match the same voltage level as redundant switching states. The symmetrical distribution of power losses between S1 is accomplished bythe usage of redundant switching states.

When devices S1, S2 are "OFF," the full-bridge submodule generates a voltage level of -V_C. When there are DC-side faults, the current is limited by this switching condition.

The full-bridge sub-module's operation is represented by the AC output voltage equation, which is given by equation 5:

$$V_F = (S_1 S_2 - \bar{S}_1 \bar{S}_2) V_C \qquad 5$$

- <u>Flying capacitor (FC) submodule</u>

The flying capacitor (FC) submodule configuration is displayed in Figure I.7 .It consists of two DC capacitors (C1 and C2) and four IGBT devices with anti-parallel diodes (S1, S1, S2, and S2). DC capacitors C1 and C2 voltage is determined by :

$$V_{C1} = \frac{1}{C1}\int_{+0}^{t} ic1(r)dr \qquad 6$$

$$V_{C2} = \frac{1}{C2}\int_{+0}^{t} ic2(r)dr \qquad 7$$

The DC capacitors current is given in terms of the device switching states and the AC current as :

$$i_{C1} = S1\, i_{xy} \qquad 8$$

$$i_{C2} = (S2 - S1)\, i_{xy} \qquad 9$$

Table I.3: Switching states of FC SM [2]

States	1	2	3	4		5	6	7	8	9
S_1	0	1	0	0		0	1	1	0	1
$\bar{S}_1$	0	0	1	0		0	1	0	0	0
S_2	0	0	0	1		0	0	1	1	0
$\bar{S}_2$	0	0	0	0		1	0	0	1	1
V_F	-	-	-	-		-	$+V_{DC}$ (V_{c1})	0 ($V_{C1} - V_{C3}$)	$-V_{DC}$ (V_{c2})	0 ($V_{C3} - V_{C2}$)
Condition	Allowed									

Table I.4displays the flying capacitor submodule's device switching states (S1 and S2). As seen in Figure I.8, there are a total of four switching combinations that result in three voltage levels:

"0," $V_{C1}-V_{C2}$ or V_{C2}, and V_{C1}. During the reverse blocking mode, the DC capacitor voltage V_{C1} is regulated at twice the DC capacitor voltage V_{C2}, producing symmetrical steps in the output voltage and equal voltage across IGBT devices. When both S1 and S2 devices are turned on, the AC output voltage is equal to "V_{C1}." In this mode, the DC capacitor voltage V_{C1} rises when the current flows in a positive direction and falls when it flows in a negative direction. The voltage of the DC capacitor V_{C2}, doesn't change. When a switching state is S1–"ON," S2–"OFF," the AC output voltage will be "$V_{C1}-V_{C2}$." In this mode, when the current is flowing in a positive direction, the DC capacitor voltage V_{C1} rises and V_{C2} falls, and vice versa. Similar to this, the AC output voltage is equal to V_{C2} for both switching states: S1–"OFF" and S2–"ON". While the DC capacitor voltage V_{C1} stays constant, the DC capacitor voltage V_{C2} will fluctuate in this mode. The AC voltage level is "0" when S1, S2 are in the "OFF" switching state. They produce the same voltage values at the output for each of the states[2]. The DC capacitor voltage is regulated by

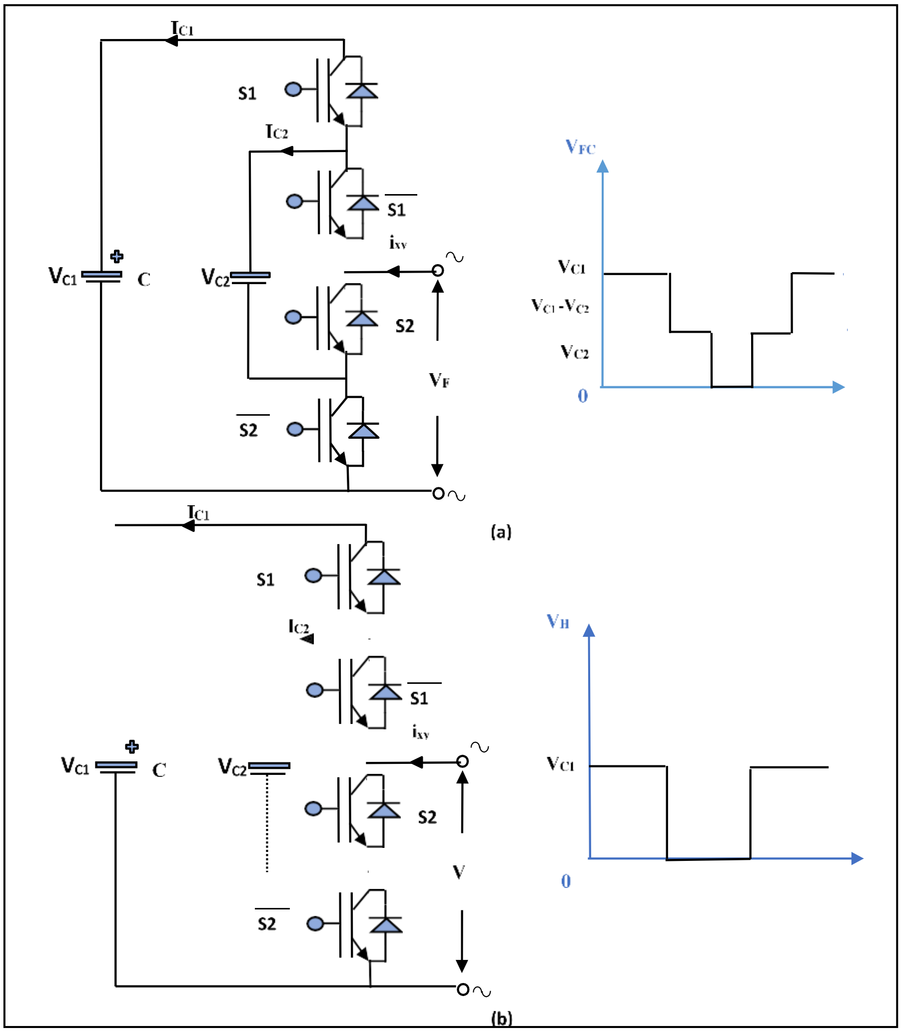

Figure I.8 : Flying capacitor submodule and output voltage waveform: (a) three-level operation, and (b) two-level operation

The switching states that correspond to these states. The flying capacitor submodule's operation is represented by the AC output voltage equation, which is given by:

$$V_{FC} = S_1V_{C1} + (S_2 - S_1)V_{C2} \qquad 10$$

The flying capacitor submodule can work as a half-bridge submodule in addition to having dual functionality. The equivalent operation of a half-bridge submodule and a flying capacitor submodule is depicted in Figure (b). The voltage levels "0" and "V_{C1}," respectively, at the output are produced by the switching combinations that correspond to the states. This mode of operation fully omits the DC capacitor C2. The half-bridge submodule's output voltage is provided by:

$$V_H = S_1S_2V_{C1} \qquad 11$$

- Cascaded half-bridge (CH) submodule

The cascaded half-bridge (CH) submodule circuit arrangement is shown in Figure I.12. It is made up of two half-bridge submodules that are the same and are linked in series.

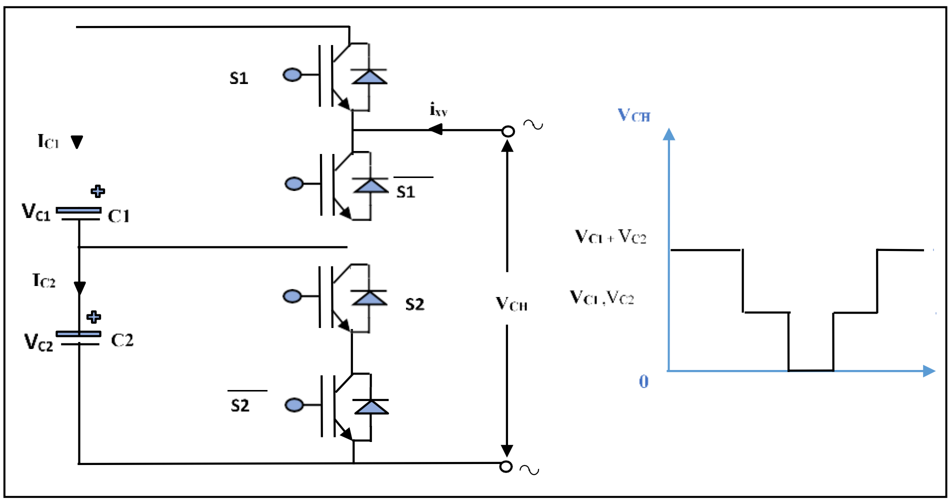

Figure I.9 :Cascaded half-bridge submodule and output voltage waveform.

The two DC capacitors (C1 and C2) in the cascaded half-bridge submodule have nominal voltages that are equivalent. The voltage of C1 and C2's DC capacitors can be found using equation. The amount of current flowing via these capacitors is determined by:

$$i_{C1} = S_1 i_{xy} \qquad 11$$

$$i_{C2} = S_{12} i_{xy} \qquad 12$$

The probable pairing of S1 and S2 switching states are shown in Table I.5. The cascaded half-bridge submodule generates three voltage states: "0," "V_{C1} and V_{C2}," and "V_{C1} + V_{C2}." It has four switching combinations. Figure I.9 displays the cascaded half-bridge submodule's AC output voltage waveform. "V_{C1} + V_{C2}" is the output voltage when devices S1, S2 are "ON." In this condition, the voltage of the DC capacitors C1 and C2 varies according to the direction of the current [2].

Table I.6: Switching states of CH SM

States	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
S1	0	1	0	0	0	1	0	0	1
$\overline{S1}$	0	0	1	0	0	1	1	0	0
S2	0	0	0	1	0	0	1	1	0
$\overline{S2}$	0	0	0	0	1	0	0	1	1
V_F	-	-	-	-	-	$2V_{DC}$ ($V_{c1+}V_{C2}$)	$-V_{DC}$ (V_{C1})	0	-
Condition	Allowed								

One of the half-bridge submodules is bypassed when switching states, so the output voltage is either "V_{C1}" or "V_{C2}." In this mode, the positive direction of the current causes the DC capacitor voltage corresponding to the inserted half-bridge submodule to increase, and vice versa. The half-bridge submodule that was bypassed maintains a steady DC capacitor voltage. When devices S1, S2 are "OFF," the cascaded half-bridge submodule generates a voltage level of "0" at the output. The voltage of the DC capacitors "V_{C1}" and "V_{C2}" does not change depending on the direction of the current. Mathematically, the cascaded half-bridge submodule's AC output voltage is expressed as:

$$V_{CH} = S_1 V_{C1} S_2 V_{C2} \qquad 13$$

- <u>Double clamp (CD) sub-module</u>

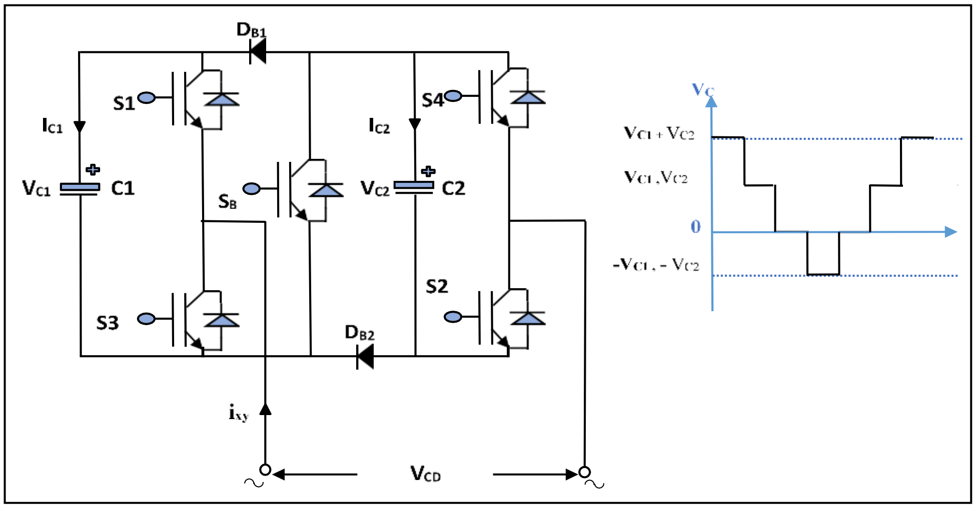

Figure I.10: Double clamp submodule and output voltage waveform

Each half-bridge submodule has one DC capacitor whose voltage can be obtained from the equation .The current owing through the DC capacitors is given by :

$$i_{C1} = S_1 i_{xy} + (1 - S_B) i_{xy} \qquad 14$$

$$i_{C2} = S_2 i_{xy} + (1 - S_B) i_{xy} \qquad 15$$

Table I.7: Switching states of CD SM

States	1	2	3	4	5	6	7	8	9	10
S1	0	0	0	1	0	0	1	0	1	1
$\overline{S1}$	0	1	0	1	1	0	0	0	0	0
S2	0	0	1	0	1	1	0	0	0	1
S2	0	0	0	0	0	1	0	1	1	0
V_F	-	-	-	$+V_{DC}$	0	$-V_{DC}$	-	-	-	-
Condition	Allowed						Potentially destructive			

The states in which the double clamp submodule switches are shown in Table I.5. The normal operation of a double clamp submodule is comparable to that of a cascaded half-bridge submodule, which has four switching possibilities and can produce three voltage levels: "0" "$V_{C1}$and V_{C2}," and "V_{C1}+ V_{C2}." In regular functioning, the IGBT device "SB" is consistently "ON." The two DC capacitors of the half-bridge submodules are linked in series via diodes DB1 and DB2 and switch SB when devices S1, S2 are "ON." The AC output voltage in this condition is equal to "V_{C1}+ V_{C2}." Turning "OFF" either S1 or S2 will bypass one of the half-bridge submodule DC capacitors, generating the voltage level "V_{C1}, V_{C2}." Disabling devices S1 and S2 will generate the voltage level "0." The double clamp submodule's typical operation is represented by the AC output voltage equation (16), which is given by :

$$V_{DC} = S_B(S_1V_{C1} + S_2V_{C2}) \qquad 16$$

In addition, the double clamp submodule produces negative voltage levels when operating in the blocking mode (BM). When there are DC-side failures, this mode of operation is employed to limit current. As seen in Table I.5, all IGBT devices are in this state and are turned "OFF" "V_{C1} + V_{C2}" represents the submodule output voltage in the positive direction of current flow, and "$-V_{C1}$, $-V_{C2}$" represents the submodule output voltage in the negative direction.

I.5.1.4. Modulation Techniques

Although there are a lot of equations and knowledge behind these pulse width modulation techniques, the physical knowledge and understanding of the operation of power converters in real-life applications are very important. This is why in the project stage, advanced pole voltage source inverters design using modern control algorithms and cascade converter concepts will be involved. Well-known carrier-based pulse width modulation techniques are used in single-phase and three-phase voltage source inverters and also in three-phase voltage source converters. These carrier-based pulse width modulation techniques use a fixed or variable position high-frequency triangular carrier waveform and compare it with one or more narrow bands of the reference modulating waveforms to generate the appropriate pulse width modulation gate signals. The triangular carrier waveform, reference modulation waveforms, and the generated pulse width modulation gate signals can be in the range of -1 to +1, and the equations for calculating the continuous phase shift sinusoidal pulse width modulation, space vector pulse width modulation, and various selective harmonic elimination pulse width modulation can be different. Traditional modulation techniques like phase shift modulation, amplitude modulation, and pulse width modulation generate trapezoidal or sinusoidal waveforms for converters. Pulse width modulation is popular in power electronics for its attractive features: linear feedback control, low total harmonic distortion, and reduced switching losses in power semiconductor devices.

I.5.2. Operating Principle

The operating principles of a modular multilevel converter involve the use of individualmodular sub-converters grouped together to achieve high voltage/high power applications suchas HVDC transmission systems and renewable energy systems. The converter consists of independent and independent voltage source transformer submodules, each with a DC source, a capacitor voltage divider and an H-bridge inverter. By connecting the AC outputs of the sub-converters in series, the final result is obtained. One of the main advantages of this converter is its modularity in terms of both sub-modules and voltage output levels, which allows easyisolation of damaged sub-modules and efficient operation. The main functions of a modular multi-level converter include three-phase conversion. From alternating current to high voltage direct current, which is then used to output variable voltage and frequency alternating current through inverter circuits. The DC interconnect contains several submodules that provide high- resolution output voltage waveforms generated by the submodules' switches and capacitors for energy storage. This configuration enables high-quality output voltage waveforms with low- power switching devices, reducing conduction losses and device voltages. In addition, the operation of switches is independent of changes in inductance and capacitance values, which improves reliability and reduces faults. Voltage conversion in a modular multilevel converter is performed by adjusting the output voltages of each submodule to achieve the desired phase voltages. . .Different modulation strategies are used to control the output waveform, such as baseband sub-modulation PWM, phase shift carrier PWM, and selective harmonic elimination modulation. By maintaining capacitor voltage balance in each submodule, the power electronic switches can work constructively together to synthesize the AC line voltage. Selective harmonic modulation with fixed switching patterns can also provide a constant output voltage, providing solutions for certain operating conditions. Modulation techniques such as selective harmonic elimination modulation and phase shift carrier PWM are used to improve output waveform quality and reduce harmonics. content These methods include calculating selected harmonic amplitudes to cancel unwanted harmonics and adjusting the phase shift between carriers to control the output voltage. By selecting different fixed switching patterns and modulation rates, the output waveform of the converter can be quickly adjusted to meet specific requirements.

I.5.2.1. Voltage balancing

Maintaining the voltage balance across the individual submodules is crucial for the proper operation of an MMC. Sophisticated control algorithms are employed to actively monitor and adjust the voltage levels in each submodule, ensuring equal distribution of the overall voltage and preventing potential failures. Voltage balancing is crucial for the operation of modular multilevel converters. It involves controlling the charging and discharging of capacitors in sub-modules to maintain balanced voltages. This can be achieved through a closed-loop PI controller in the control stage, or using a logic-based algorithm in the modulation phase. The logic function approach is suitable for any PWM system, while the PI controller method is specifically for PSC-PWM.

A simple voltage balancing strategy involves measuring capacitor voltages in each branch, comparing them, sorting submodule index numbers based on arm flow direction, and adjusting the number of submodules in the modulation stage. This ensures that submodules with lower capacitor voltages are charged in the positive current direction, while those with higher voltages are discharged in the negative direction. By comparing reference index numbers generated by each submodule, the necessary gate signals for each submodule can be determined to maintain a constant switching frequency equal to the carrier frequency of the PWM system. Overall, voltage balancing is a critical aspect of ensuring the reliability and efficiency of modularmultilevel converters, and the use of either a closed-loop PI controller or a logic-based algorithm can help achieve this balance effectively [1].

I.5.2.2. control strategies employed in modular multilevel converters

The control strategies commonly used for MMC:

- **Pulse Width Modulation (PWM):** Pulse Width Modulation is a fundamental control strategy used in modular multilevel converters (MMC) to regulate the output voltage and current. PWM involves switching the power devices on and off at a high frequency while varying the duty cycle to control the average output voltage and current of the converter. This strategy allows for precise control of the output to match the desired load demand, enabling efficient power conversion and high-quality output waveforms. Figure I.14, shows the output voltage of MMC during PWM control strategy.

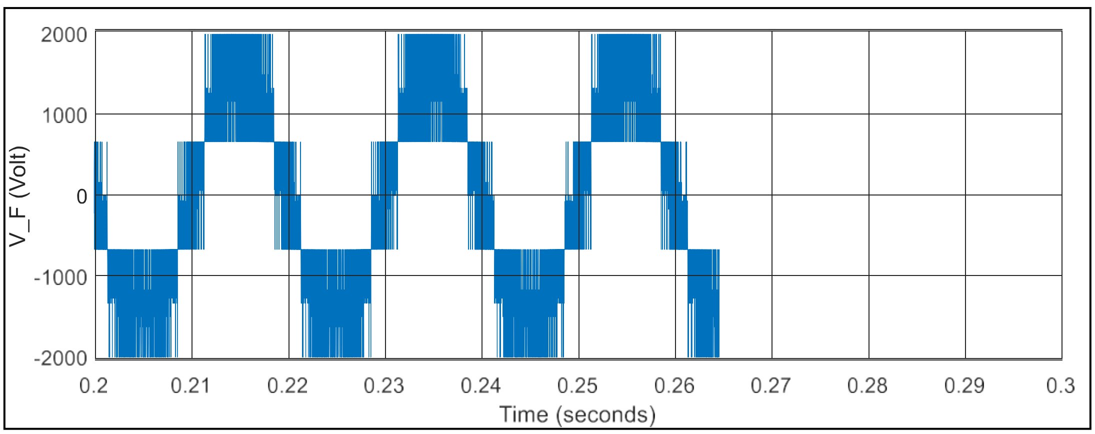

Figure I.10 : Output voltage of MMC based Pulse Width Modulation (PWM) Control

- **Current Control Techniques:** Current control techniques focus on regulating the current flow within the MLC to ensure stability and optimal performance. By controlling the current levels, these techniques help manage power flow, reduce harmonics, and enhance the overall efficiency of the converter. Current control strategies are essential for maintaining system stability and ensuring safe operation in high-power applications.
- **Voltage Control Techniques:** Voltage control techniques are employed in MLCs to manage the output voltage levels effectively. These strategies aim to regulate the voltage output to meet specific requirements, ensuring stable operation and optimal performance of the converter. Voltage control techniques play a critical role in maintaining the desired voltage levels, reducing harmonics, and improving the overall power quality of the system.

I.5.3. Comparison with Conventional Converters

I.5.3.1. Advantages of Modular Multilevel Converters (MMCs)

- Quality Output Performance: MMCs offer high-quality voltage and current output, ensuring superior power conversion efficiency and waveform quality.
- Modularity and Scalability: MMCs are modular and scalable, allowing for easy extension to higher voltage and power levels by adding more submodules in series or parallel.
- Lower Switching Losses: MMCs exhibit higher efficiency and reliability due to lower switching losses, enhancing overall system performance.
- Reduced Voltage Stress: MMCs impose lower voltage stress on power devices, contributing to improved reliability and longevity of the components.
- Fault-Tolerance and Redundancy: MMCs inherently offer fault-tolerance and redundancy, ensuring system stability and reliability even in challenging conditions.

I.5.3.2. Disadvantages of Modular Multilevel Converters (MMCs):

- Higher Complexity and Cost: MMCs entail higher complexity and cost due to the number of components required, sophisticated control algorithms, and communication systems.
- Dynamic Interactions and Harmonics: MMCs can introduce dynamic interactions and harmonics in the system, potentially affecting stability and power quality.
- Safety Concerns: The high voltage and current levels in MMCs necessitate effective protection and safety mechanisms to prevent faults and ensure safe operation.
- Complex Control Requirements: MMCs require advanced control strategies to manage the switching of submodules and circulating currents effectively, adding to the complexity of operation.

I.5.4. Mathematical Modeling

Mathematical modeling of Modular Multilevel Converters (MMCs) is a complex task that involves representing the dynamic behavior of the converter’s components and the control strategies employed. The model typically includes the following elements:

- **Submodule Capacitance (C):** Each submodule’s capacitor voltage needs to be modeled to ensure voltage balancing across the converter.
- **Arm Inductance (L):** The inductance of the arms affects the current ripple and the dynamic response of the MMC.
- **Switching Functions (S):** These represent the state of the IGBTs within each submodule, which are crucial for synthesizing the output voltage waveform.

- **Control System:** The control system model includes the algorithms for capacitor voltage balancing, power flow control, and modulation techniques.

The mathematical model can be expressed using differential equations that describe the behavior of the MMC under different operating conditions. For instance, the state-space representation is a common approach where the state variables typically include the capacitor voltages and the branch currents.

Here's a simplified example of the state-space equations for an MMC:

$$\frac{d}{dt}V_C(t) = \frac{1}{C}I_{arm}(t) - \frac{1}{C}S(t)V_{out}(t) \qquad 17$$

$$\frac{d}{dt}I_{arm}(t) = \frac{1}{L}V_{dc}(t) - \frac{1}{L}S(t)V_C(t) - \frac{R}{L}I_{arm}(t) \qquad 18$$

Where:

- $V_C(t)$ is the capacitor voltage at time (t)
- $I_{arm}(t)$ is the arm current at time (t)
- $S(t)$ is the switching function at time (t)
- $V_{out}(t)$ is the output voltage at time (t)
- $V_{dc}(t)$ is the DC link voltage at time (t)
- R is the resistance of the arm

I.6. CONCLUSIONS

As conclusion, power electronic converters serve as the cornerstone of contemporary electrical systems, facilitating efficient energy conversion and management across diverse applications. By regulating voltage, current, and frequency, these converters enable the seamless integration of renewable energy sources, improve electric drive performance, and optimize power distribution networks. Their significance extends across industrial, commercial, and residential sectors, where they play a crucial role in enhancing energy efficiency and mitigating environmental impact. Ongoing advancements in semiconductor technology, control algorithms, and system integration have propelled power electronic converters to unprecedented levels of performance and reliability. Ultimately, the future of power electronic converters holds the promise of a more resilient, adaptable, and sustainable energy infrastructure, ushering us toward a greener and more electrified world. As we push the boundaries of technological innovation, power electronic converters will remain indispensable in shaping the landscape of modern power systems for generations to come.

CHAPTER II

MACHINE LEARNING FAULT DIAGNOSIS

CHAPTER II: MACHINE LEARNING FAULT DIAGNOSIS

II. Machine Learning Fault Diagnosis

II.1. Introduction

Within electrical engineering, ensuring the dependable operation of power converters is crucial, particularly in systems where energy conversion is central. Faults, ranging from short circuits to component deterioration, have the potential to disrupt the smooth functioning of these converters, leading to hazards and inefficiencies. Therefore, grasping the intricacies of fault detection is vital for maintaining system integrity and operational safety. Fault detection involves identifying abnormalities or deviations from normal operating conditions within a system. In the context of multilevel power converters, this entails identifying faults such as overvoltage, undervoltage, overcurrent, and short circuits. The significance of fault detection cannot beoverstressed; it not only ensures the longevity and reliability of the power system but also guardsagainst catastrophic failures with far-reaching consequences. Engineers have developed numerous strategies to effectively detect and address faults. These techniques encompass both hardware-based and software-based approaches, each offering distinct advantages and applications. Hardware solutions often entail deploying specialized sensors and monitoring circuits to detect abnormalities in voltage, current, and temperature. Conversely, software-based methods utilize advanced algorithms and signal processing techniques to analyze system behavior and detect anomalies in real-time. These methods may include model-basedapproaches, such as observer-based fault detection, as well as data-driven methods like machine learning and neural networks.

II.2. Machine Learning (ML)

Machine learning, a subset of artificial intelligence (AI), focuses on crafting algorithms and methodologies enabling computers to learn from data and generate predictions or decisions. Unlike conventional programming, which relies on explicit instructions tailored to specific tasks,machine learning algorithms autonomously discern patterns and relationships from data without explicit programming for each scenario.

The fundamental principle underlying machine learning is to empower computers to learn from data and enhance their performance progressively. This is achieved through statistical models and algorithms capable of autonomously recognizing patterns, correlations, and trends within datasets. Through the analysis of extensive data sets, machine learning algorithms can uncover valuable insights and make predictions or decisions that may elude human observation or manualanalysis. (Figure II.14) Depicts four machine learning techniques and describes briefly the natureof data they require [5].

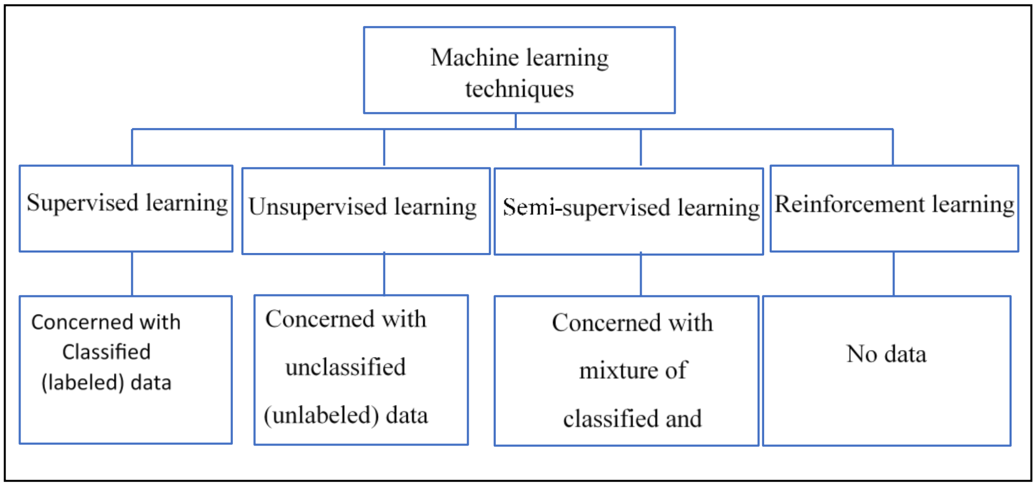

Figure II.1 : Different machine learning techniques and their required

II.3. Types of machine learning

Machine learning involves training algorithms on large data sets, learning patterns, and data relationships to make predictions or decisions based on new, unseen data. These algorithms can be broadly divided into several types, including [5]:

II.3.1. Supervised machine learning

Supervised Learning involves training algorithms on labeled datasets, where each data point is paired with a corresponding label or outcome. The objective is to establish a mapping from input features to output labels. For instance, this could entail tasks like distinguishing between spam and non-spam emails, or forecasting housing prices based on factors such as location, size, and number of bedrooms.

II.3.2. Unsupervised machine learning

In Unsupervised Learning, algorithms are trained on unlabeled datasets, where no predefined labels or outcomes exist. Instead, the algorithm's objective is to unveil hidden patterns orstructures within the data. This could involve tasks such as grouping similar data points together through clustering techniques or employing dimensionality reduction methods to extract significant features.

II.3.3. Semi-supervised learning

Semi-Supervised Learning merges aspects of both supervised and unsupervised learning. It involves training algorithms on datasets comprising both labeled and unlabeled data. This approach proves beneficial when labeled data is limited or costly to acquire, as it enables the algorithm to utilize both types of data to enhance performance.

II.3.4. Reinforcement machine learning

Reinforcement Learning stands as a branch of machine learning in which an agent learns to make decisions through interaction with an environment and obtaining feedback in the form of rewards or penalties. The objective is to acquire a policy or strategy that maximizes cumulative rewards over time. Examples include instructing a robot to navigate a maze or training an AI to excel in video games.

II.4. Machine Learning Classification

Classification in machine learning is a fundamental technique aimed at sorting data points into predefined categories. This process entails training a model on a labeled dataset, where each data point is linked to a specific class or category. Through this training, the model discerns patterns and connections within the data, enabling it to predict the class labels of new, unseen data points.

Classification tasks vary widely in complexity, ranging from straightforward binary classification, such as distinguishing between spam and non-spam emails, to more intricate multi-class classification, like identifying different species of animals. The selection of a classification algorithm depends on various factors, including the dataset's characteristics, the number of classes, and the problem's complexity.

Common classification algorithms encompass a range of techniques:

- **Logistic Regression:** A linear model estimating the probability of a binary outcome based on predictor variables.
- **Decision Trees:** Tree-like structures where each internal node represents a feature, and branches and leaf nodes signify decisions and class labels, respectively.
- **Random Forest:** An ensemble method creating multiple decision trees during training and combining their outputs.
- **Support Vector Machines (SVM):** A supervised learning model that segregates data points into classes by finding the optimal hyperplane.
- **Neural Networks:** Deep learning models with interconnected layers of neurons, capable of learning intricate patterns and relationships within the data.

II.5. Classification Types

Classification in machine learning encompasses various types, each tailored to specific aspects of the classification problem and the structure of output classes. Below are some common classification types:

II.5.1. Binary Classification: This type involves sorting data points into one of two possible classes or categories. Examples include distinguishing between spam and non-spam emails, predicting customer churn, or diagnosing medical conditions.

II.5.2. Multi-Class Classification: In multi-class classification, data points are categorized into one of three or more classes or categories. Examples include classifying different animal species, categorizing news articles into various topics, or identifying music genres.

II.5.3. Multi-Label Classification: Multi-label classification assigns multiple labels to each data point, often suitable for tasks where data points can belong to multiple categories simultaneously. Examples include classifying images with multiple objects, tagging articles with relevant topics, or labeling products with multiple attributes.

II.5.4. Imbalanced Classification: Imbalanced classification deals with datasets where one class significantly outnumbers the others, requiring specialized techniques to handle the imbalance and ensure accurate predictions for minority classes.

II.5.5. Hierarchical Classification: This type organizes classes into a hierarchical structure, facilitating a more organized and structured approach to classification, particularly in domains with complex relationships between classes and a large number of classes.

II.5.6. Ordinal Classification: Ordinal classification addresses datasets where classes possess a natural ordering or hierarchy. The objective is to predict the ordinal relationship between classes rather than assigning arbitrary labels. Examples include ranking products by customer satisfaction or predicting disease severity.

II.6. Learning Data in Supervised and Unsupervised Learning

Here are the fundamental differences between supervised learning (and) unsupervised learning(in the context of modular multilevel converters (MMCs)

1. Supervised Learning

- Definition: Supervised learning relies on labeled datasets, where each data point includes both input features and corresponding output labels.
- Purpose: The objective is to train algorithms to classify data or predict outcomes accurately.
- Examples:
  - Classification: Algorithms categorize test data into specific groups (e.g., identifying faults in MMCs as either open-circuit or short-circuit).
  - Regression: Models predict numerical values based on input data (e.g., predicting the temperature rise in an MMC under different load conditions).
- Common Algorithms

- For classification: Linear classifiers, support vector machines, decision trees, random forests.

- For regression: Linear regression, logistic regression, polynomial regression.

2. Unsupervised Learning:

- Definition:(Unsupervised learning analyzes) unlabeled datasets without predefined output labels.

- Tasks:

- Clustering: Grouping similar data points based on inherent similarities or differences (e.g., clustering operating conditions of MMCs to identify common patterns).

- Association: Discovering patterns or associations within the data.

- Dimensionality Reduction: Reducing the number of features while preserving essential information (e.g., simplifying the feature set for monitoring MMC performance).

- Use Cases

- Market segmentation, image compression, anomaly detection, etc.

II.7. Machine Learning Data Quantitative Requirements

Machine learning (ML) data requirements for modular multilevel converters (MMC)s involve several crucial considerations. Let's explore them:

1. Dataset Size

- The size of your training dataset significantly impacts ML model performance. For MMC-related tasks, ensure:

- Sufficient Samples: Have an adequate number of samples representing various operating conditions, fault scenarios, and system dynamics.

- Imbalance: Address class imbalance if present (e.g., normal operation vs. fault conditions).

- Generalization: Aim for a dataset that generalizes well to unseen scenarios.

2. Feature Selection

- Choose relevant features that capture the behavior of MMCs, including:

- Voltage and Current Waveforms: To capture transient and steady-state behavior.

- Switching Patterns: Representing converter operation.

- Environmental Factors: Such as temperature and humidity.

3. Data Quality

- Clean and preprocess your data:

- Outliers: Detect and handle outliers.
- Missing Data: Impute missing values.
- Noise Reduction: Apply filters or denoising techniques.

4. Temporal Resolution

- Decide on the temporal resolution of your data:
  - Sampling Rate: Determine how frequently data is collected (e.g., per second, minute, etc.).
  - Transient vs. Steady-State: Ensure the capture of both transient and steady-state behavior.

5. Labeling

- For supervised learning, ensure accurate labels:
  - Fault Labels: Identify fault types (e.g., open-circuit, short-circuit).
  - Operating Modes: Different MMC modes (e.g., grid-connected, islanded).

6. Validation and Testing

- Reserve a portion of your data for validation and testing.
- Use techniques like cross-validation to assess model performance.

II.8. Metrics in classification problems

Evaluation metrics commonly used in classification problems are crucial for assessing the performance of machine learning models, especially in binary or multiclass classification tasks. Here are some key metrics:

1. Accuracy

- Accuracy measures how often the classifier correctly predicts the class labels.
- Defined as the ratio of the number of correct predictions to the total number of predictions.
- However, accuracy alone can be misleading, especially in class-imbalanced datasets with a significant disparity between positive and negative labels.
- Example: A model with 99% accuracy might seem excellent, but context matters.

2. Precision and Recall

- Precision: The proportion of true positive predictions (correctly predicted positive instances) out of all positive predictions.
- Recall (Sensitivity: The proportion of true positive predictions out of all actual positive instances.
- These metrics are particularly useful for imbalanced datasets.

- Precision focuses on minimizing false positives, while recall aims to minimize false negatives.

- The F1-score combines precision and recall into a single metric, balancing both aspects.

3. Confusion Matrix

- A table summarizing the performance of a classification algorithm.

- Shows true positive (TP), true negative (TN), false positive (FP), and false negative (FN) counts.

- Useful for understanding the trade-offs between different metrics.

4. Log-Loss (Cross-Entropy Loss)

- Commonly used for probabilistic models.

- Measures the difference between predicted probabilities and actual class labels.

- Penalizes confident incorrect predictions more than uncertain ones.

5. AUC-ROC (Area Under the Receiver Operating Characteristic Curve)

- Evaluates the model's ability to distinguish between positive and negative classes across different probability thresholds.

- Summarizes the trade-off between true positive rate (recall) and false positive rate.

- AUC values close to 1 indicate better performance.

II.9. Training Data Preparation

Data preparations crucial for the successful implementation of machine learning models, including those related to modular multilevel converters (MMCs) Let's delve into how data preparation specifically applies to MMCs:

1. Challenges in MMC Simulation:

- Simulating the electromagnetic transients of MMCs in high-voltage direct current (HVDC) systems can be demanding due to the high number of nodes and semiconductor devices involved.

- To mitigate this challenge, researchers have developed various MMC models that strike a balance between simulation speed and accuracy.

- A common feature among these models is the simplification of semiconductor device representations within the MMC.

- These models are designed for specific tasks, such as power flow analysis, stability assessments, and electromagnetic transient (EMT) simulations.

2. Trade-offs in Model Selection:

- Different MMC models are suitable for different simulation tasks based on the trade-off between accuracy and efficiency.

- For steady-state power flow (PF) analyses, simpler models are preferred as they focus on grid steady-state operation.

- In contrast, EMT simulations require more detailed models to capture fast dynamics.

- The choice of model depends on the specific application and computational requirements.

3. Isomorphism-Based Approach:

- A novel approach for MMC simulation involves sub-circuit isomorphism.

- Initially used for analyzing modular electronic circuits (e.g., random access memories), this approach clusters structurally identical sub-modules within the MMC.

- By leveraging common behavior, it enables detailed yet efficient simulations of HVDC systems.

- This method provides a balance between accuracy and computational cost.

II.10. The K Nearest Neighbors (KNN)

II.10.1. Definition

K-Nearest Neighbors (K-NN) is celebrated as one of the simplest and most straightforward Machine Learning algorithms, making it highly accessible for implementation. Despite its simplicity, K-NN boasts versatility and resilience, rendering it a formidable tool for both classification and regression tasks. The algorithm's acronym, "K-Nearest Neighbors," succinctly encapsulates its essence. Its adaptability stems from its capacity to handle diverse tasks, ranging from classification to regression. Fundamentally, K-NN operates on the premise that similar entities tend to cluster together in proximity. However, it's important to note that K-NN's utility comes at the cost of memory consumption during training. As datasets grow in size, K-NN's performance may suffer due to its need to compute distances between test and training data, resulting in slower execution times. The parameter "K" in K-NN signifies the number of neighbors considered in the algorithm. Determining the optimal value of K often entails a trial- and-error approach, as it is a hyperparameter that is not learned directly from the data.

II.10.2. Theoretical component of the K-NN algorithm

The K-Nearest Neighbors (K-NN) algorithm stands as a straightforward yet potent tool utilized for both classification and regression tasks within machine learning. Central to its operation is the principle of similarity: akin data points tend to yield akin outcomes.

The conceptual framework of the k-NN algorithm encompasses several pivotal elements:

1. **Distance Metric:** To gauge the resemblance between data points, a distance metric becomes imperative. While Euclidean distance stands as the most prevalent choice, alternative metrics like Manhattan distance or cosine similarity find utility based on data characteristics and task nuances.

2. **K-Nearest Neighbors:** The 'K' parameter in K-NN denotes the quantity of Nearest Neighbors taken into account during predictions. Upon encountering a query point, the algorithm discerns the k nearest neighbor's contingent on the designated distance metric.

3. **Voting Mechanism:** Upon identifying the K nearest neighbors, the algorithm resorts to a voting mechanism to deduce the class label (in classification scenarios) or the value (in regression contexts) of the query point. In classification, the predominant class among the K Nearest Neighbors commonly dictates the class label assignment.

4. **Parameter Tuning:** The selection of 'K' wields significant influence within K-NN. A diminutive 'K' value may precipitate overfitting, whereas an expansive 'K' value may foster underfitting. Ergo, opting for an apt 'K' value via methodologies like cross-validation is indispensable.

5. **Scalability:** The scalability of K-NN poses a prominent challenge, particularly concerning voluminous datasets. Given the algorithm's prerequisite of computing distances between the query point and all other data points, the computational overhead can be substantial, notably within high-dimensional spaces.

6. **Data Normalization:** Normalizing feature values frequently prove requisite to preclude features with substantial scales from overshadowing distance computations. Prevalent normalization techniques encompass min-max scaling or z-score normalization.

7. **Handling Missing Values:** Addressing missing values emerges as another facet within K-NN. Imputation techniques such as mean imputation or median employment can rectify missing values preceding algorithmic application.

II.11. Decision Trees algorithm

The decision tree algorithm stands as a cornerstone within data mining, particularly in the realm of classification systems. This algorithm, renowned for its versatility, excels in handling large volumes of data, making it a vital tool in drawing insights from categorical class names. By leveraging training sets and class labels, it not only makes educated assumptions but alsoefficiently categorizes newly acquired data. Within the vast landscape of machine learningclassification algorithms, the focus of this paper rests on the decision tree algorithm and its overarching significance (Figure 12) illustrate a structure of DT.

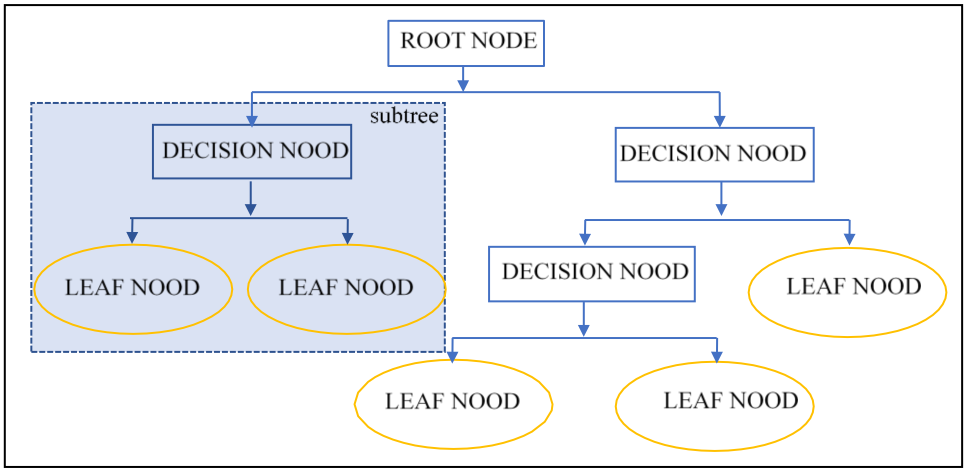

Figure II.2: illustrate a structure of DT

II.12. Decision Tree Types

In machine learning, decision trees are categorized into two main types:

II.12.1. Classification Trees

These trees are employed when the target variable is categorical, determining the occurrence or non-occurrence of an event, typically resulting in a binary outcome.

For instance, a classification tree might predict a student's course pass or fail based on factors such as study hours per week, test scores, and attendance.

II.12.2. Regression Trees

Regression trees come into play when the target variable is continuous, forecasting numerical values using historical data or information sources. For example, a regression tree could forecast the price of a house based on attributes like location, size, and number of bedrooms.

Both classification and regression trees are encompassed within the "classification and regression trees" (CART) framework. The primary distinction lies in classification trees predicting categorical results, while regression trees forecast continuous numerical outcomes.

II.13. Advantages and disadvantages of Decision Trees

II.13.1. Advantages of Decision Trees

- Interpretability: Decision trees are highly intuitive and easy to understand, allowing for clear visualization of decision-making processes.
- Minimal Data Preparation: Unlike other algorithms, decision trees require minimal data preparation, eliminating the need for normalization or handling missing values.

- Non-Parametric Nature: Decision trees do not rely on strict assumptions like linear regression, making them adaptable to various data distributions.
- Versatility: They can be used for multiple purposes, from data exploration to solving both regression and classification problems, offering a wide range of applications.
- Handling Non-Linearity: Decision trees are capable of managing complex decision boundaries, making them effective for solving non-linear problems.

II.13.2. Disadvantages of Decision Trees

1. Overfitting: Decision trees are prone to overfitting due to high variance, especially when the trees are deep and there are many features.
2. Feature Reduction and Data Resampling: Training decision trees can be time-consuming, often requiring feature reduction and data resampling to achieve efficient performance, particularly with imbalanced datasets.
3. Optimization Challenges: Decision trees use a greedy algorithm that focuses on local optimal solutions, which may not always lead to the best global result.
4. Computational Expense: Decision trees can be computationally expensive, especially with large datasets, affecting scalability and efficiency. These factors should be considered when selecting decision trees for model development to optimize results and address potential limitations.

II.14. CONCLUSIONS

In conclusions, Machine Learning (ML) fault diagnosis offers a groundbreaking approach across industries, providing a data-centric method to efficiently detect and rectify system irregularities. Utilizing ML algorithms like neural networks, decision trees, and support vector machines alongside comprehensive datasets containing historical performance data and sensor readings, fault diagnosis systems excel in anomaly detection, failure prediction, and proactive maintenance. The adoption of ML-driven fault diagnosis shows immense potential across diversesectors such as manufacturing, healthcare, and automotive, where early fault detection translates to improved reliability, reduced downtime, and heightened operational efficiency. Nonetheless, challenges persist, including the necessity for robust feature engineering, managing imbalanced datasets, and ensuring the interpretability of ML models, especially in safety-critical settings. Despite these hurdles, continual advancements in ML techniques, paired with the proliferation of sensor technology and big data analytics, highlight the ever-expanding capabilities of ML fault diagnosis to revolutionize predictive maintenance methodologies and propel innovation in theera of intelligent, self-regulating system

CHAPTER III
SIMULATION AND THE RESALTS OBTAINED

III. Simulation and the results obtained

III.1. Introduction

In this chapter, simulation results of healthy MMC are presented. Then a failure of upper and lower capacitors results are considered. Finally, a diagnosis method using machine learning approach is detailed.

III.2. Simulation results with healthy MMC

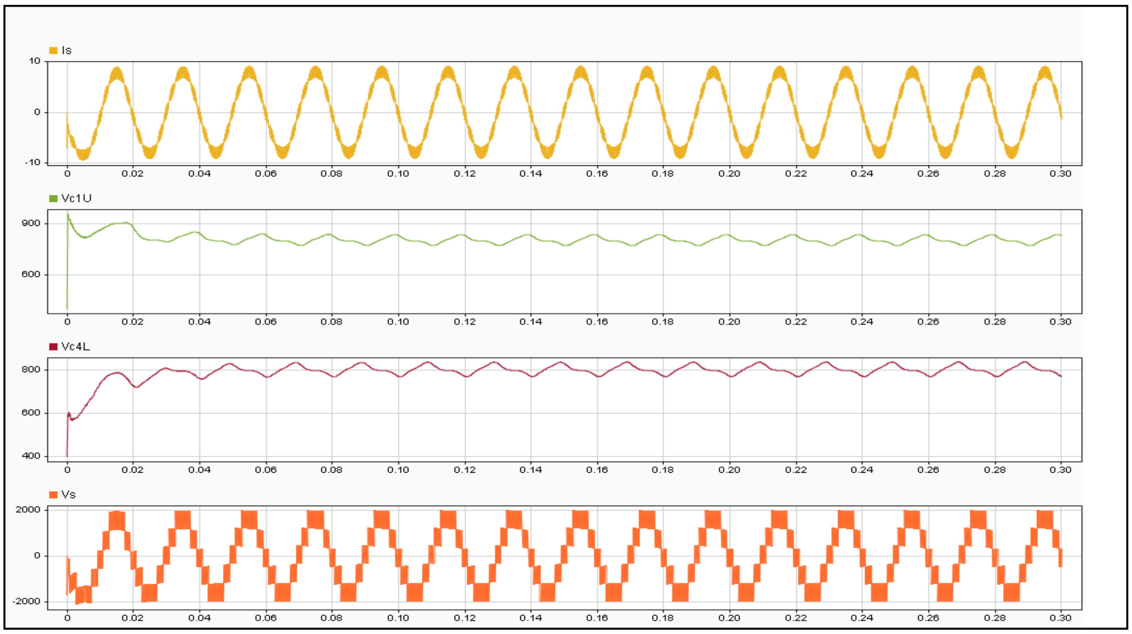

Figure III.1: the output of natural simulation of MMC

The figure III.17 shows simulation results of MMC under normal operating conditions during (0.3s):

1 - The first curve represents the output current (I_s), which present a periodic sine form with an amplitude [9.1,-9.1] and a constant frequency 50 Hz, which indicates a stable alternating current.

2- The second curve V_{C1} is upper capacitor voltage that is regulated to 800 V (V_{dc}/5).

3- The third curve V_{C4} is lower capacitor voltage that is regulated to 800 V (V_{dc}/5).

4-the fourth curve is output voltage V_s, where 6 levels are shown, with an amplitude of [2000 -2000] and a constant frequency equal to 50Hz.

III.3. Simulation results with the fault in SM1

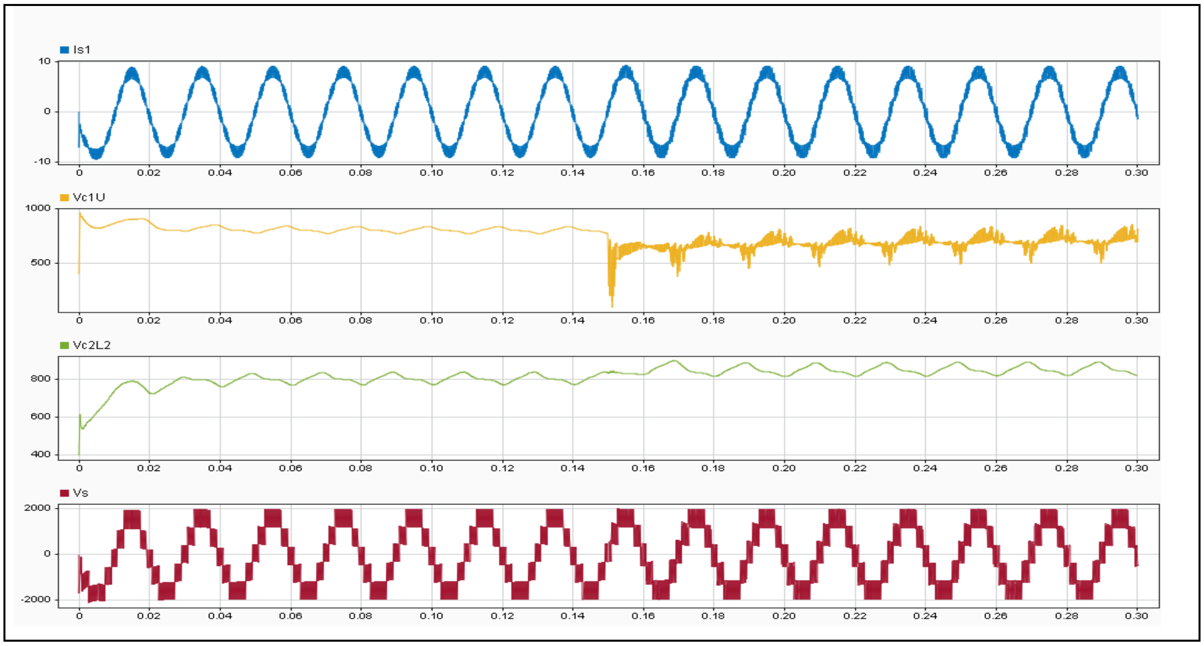

Figure III. 2 the output of simulation of MMC with the fault in SM1

The figure III.18 shows simulation results of MMC under one of upper capacitor failure conditions, this failure is introduced at 0.15s:

1 - The first curve represents the output current (I_s), which present a periodic sine form with an amplitude [9.1, -9.1] and a constant frequency 50 Hz, which indicates a stable alternating current and show currant harmonics during the failure around 0.15s to 0.30s.

2- The second curve V_{C1} is upper capacitor voltage that is regulated to 800 V (V_{dc}/5) and show voltage harmonics during the failure around 0.15s to 0.30s there a clear drop up to [100-200 V] .

3- The third curve V_{C2} is lower capacitor voltage that is regulated to 800 V (V_{dc}/5) and show harmonics during the failure are relative altitudes of up to 850V that around 0.15s to 0.30s.

4-the fourth curve is output voltage V_s, where 6 levels are shown, with amplitude of [2000 -2000] and a constant frequency equal to 50Hz than show voltage harmonics during the failure around 0.15s to 0.30s.

III.4. Simulation results with the fault in SM7

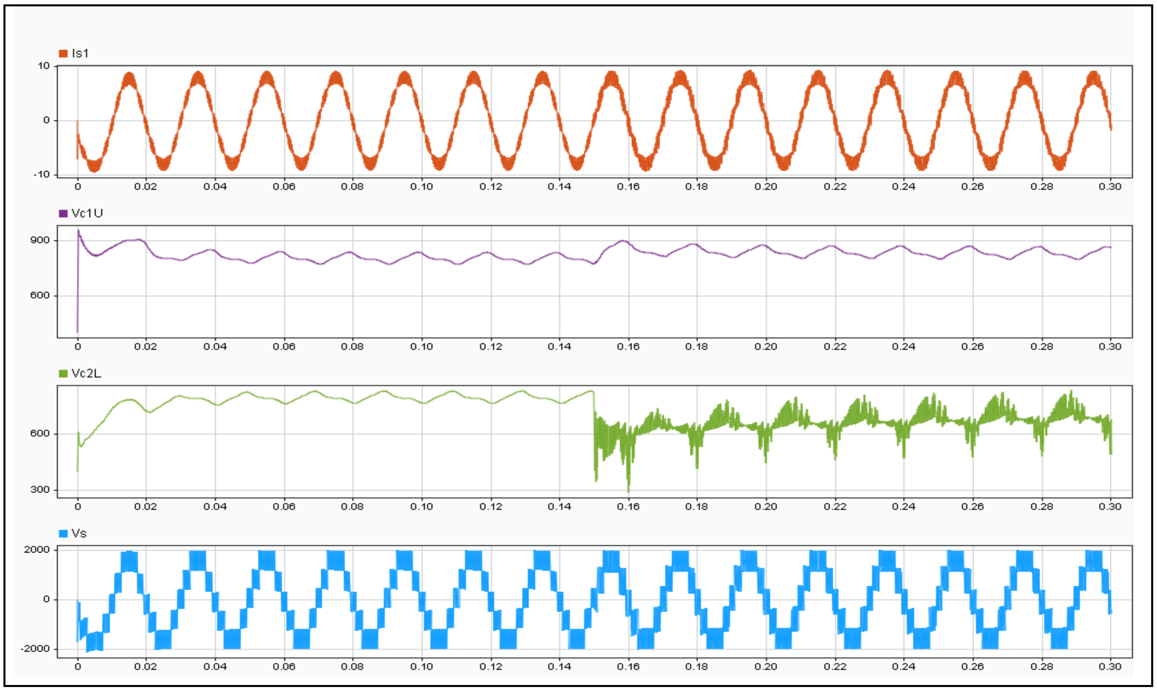

Figure III.3 the output of simulation of MMC with the fault in SM7

The figure III.19 shows simulation results of MMC under one of lower capacitor failure conditions; this failure is introduced at 0.15s:

1 - The first curve represents the output current (I_s), which present a periodic sine form with an amplitude [9.1, -9.1] and a constant frequency 50 Hz, which indicates a stable alternating current and show currant harmonics during the failure around 0.15s to 0.30s .

2- The second curve V_{C1} is lower capacitor voltage that is regulated to 800 V ($V_{dc}/5$) and show the voltage harmonics during the failure are relative altitudes of up to 850-900V that around 0.15s to 0.30s.

3- The third curve V_{C2} is upper capacitor voltage that is regulated to 800 V ($V_{dc}/5$) and show voltage harmonics during the failure around 0.15s to 0.30s there a clear drop up to [100-200 V].

4- The fourth curve is output voltage V_s, where 6 levels are shown, with amplitude of [2000 -2000] and a constant frequency equal to 50Hz than show there increase in volume disturbances or noise spikes that are particularly noticeable around 0.15s to 0.30s.

III.5. Simulation results with the fault in SM1 and SM7

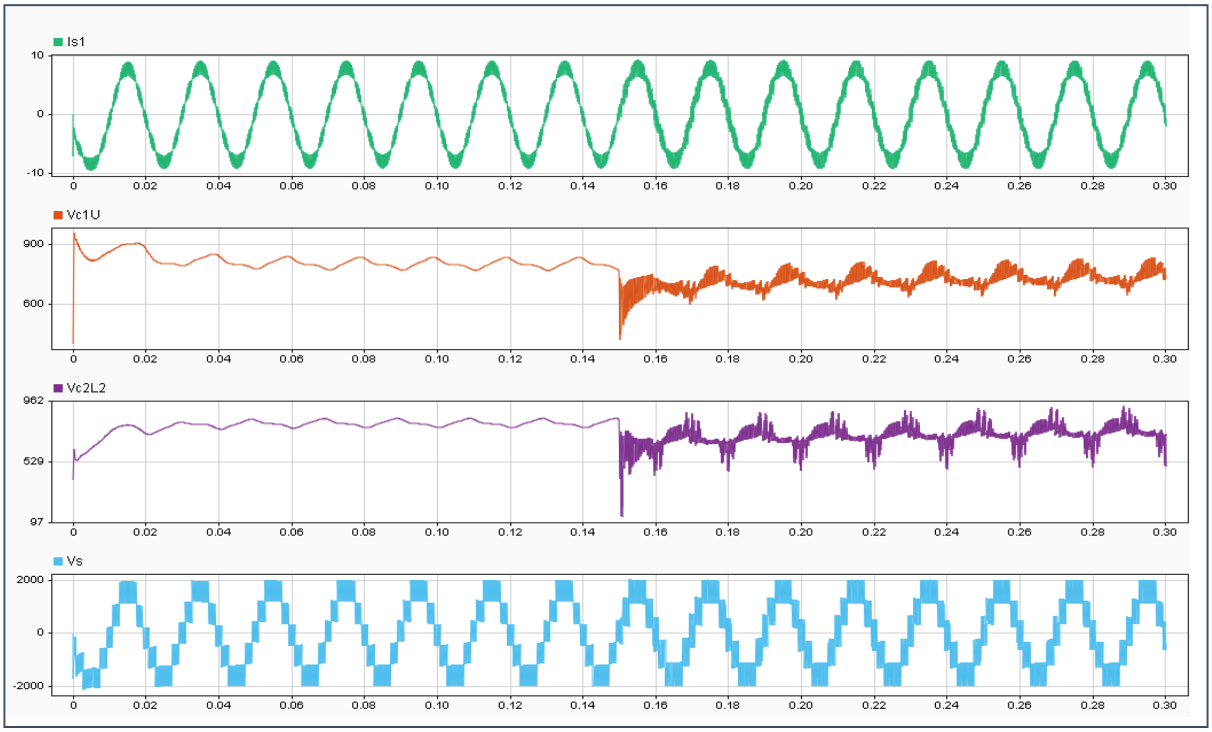

Figure III.4 the output of simulation of MMC with the fault in SM1 and SM7

The figure III.20 shows simulation results of MMC under upper and lower capacitors failure conditions; this failure is introduced at 0.15s:

1. The first curve represents the output current (I_s), which present a periodic sine form with an amplitude [9.1, -9.1] and a constant frequency 50 Hz, which indicates a stable alternating current and show currant harmonics during the failure around 0.15s to 0.30s.
2. The second curve V_{C1} is lower capacitor voltage that is regulated to 800 V (V_{dc}/5) and show the voltage harmonics during the failure are relative altitudes of down to 850-900V that around 0.15s to 0.30s.
3. The third curve V_{C1} is upper capacitor voltage that is regulated to 800 V (V_{dc}/5) and show voltage harmonics during the failure around 0.15s to 0.30s there a clear drop down to [100-150 V] .
4. The fourth curve is output voltage V_s, where 6 levels are shown, with amplitude of [2000 -2000] and a constant frequency equal to 50Hz than show there increase in volume disturbances or noise spikes that are particularly noticeable around 0.15s to 0.30s.

III.6. Fault diagnosis using machine learning algorithms

III.6.1. KNN algorithm with PYTHON

Machine learning algorithm (KNN) is applied in this section in order to develop a diagnosis method with high accuracy using PYTHON

The following is algorithm of KNN and its results

```
#############################KNN_Diagnosis################################
############
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.utils import shuffle
# read CSV data into a pandas DataFrame
data = pd.read_csv('/content/MMC.csv',sep=',')
data=shuffle(data)
# extract features and target variable
X = data[['Vc1U','Vc3L']] #.values.reshape(-3, 3)  # one feature
y = data['Label'].values
# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)

# Create a KNN classifier with K=3
knn = KNeighborsClassifier(n_neighbors=3)

# Train the classifier
knn.fit(X_train, y_train)

# Make predictions on the test set
y_pred = knn.predict(X_test)

# Print the predicted labels
print("Predicted labels:", y_pred)

# Print the accuracy of the classifier
accuracy = knn.score(X_test, y_test)
print("Accuracy:", accuracy)

########################################################################
####
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
```

```
from sklearn.metrics import recall_score
from imblearn.metrics import specificity_score
from sklearn.metrics import accuracy_score

a=recall_score(y_test, y_pred, average='macro')
b=f1_score(y_test, y_pred, average='macro')
c=precision_score(y_test, y_pred, average='macro')
d=specificity_score(y_test, y_pred, average='macro')
e=accuracy_score(y_test, y_pred)

print("recall_score:", a)
print("precision_score:", b)
print("f1_score:", c)
print("specificity_score:", d)
print("accuracy_score:", e)
```

Results

```
Predicted labels: ['TF' 'TF' 'H' ... 'OUF' 'H' 'TF']
Accuracy: 0.9991663887962654
recall_score: 0.9991624176683747
precision_score: 0.9991555281904021
f1_score: 0.9991494250103802
specificity_score: 0.9997240494688098
accuracy_score: 0.9991663887962654
```

III.6.2. Decision_Tree algorithm with PYTHON

Machine learning algorithm (Decision_Tree) is applied in this section in order to develop a diagnosis method with high accuracy using PYTHON

The following is algorithm of Decision_Tree and its results

```
#########################Decision_Tree####################################
########
import pandas as pd
from sklearn.tree  import  DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle


# read CSV data into a pandas DataFrame
data = pd.read_csv('/content/MMC.csv',sep=',')
data=shuffle(data)
```

```
# extract features and target variable
X = data[['Vc1U','Vc3L']] #.values.reshape(-3, 3)  # one feature
y = data['Label'].values
# split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)

# create decision tree classifier
clf = DecisionTreeClassifier()

# train classifier
clf.fit(X_train, y_train)

# Make predictions on the test set
y_pred = clf.predict(X_test)

# evaluate performance on testing set
accuracy = clf.score(X_test, y_test)
print(f"Accuracy on testing set: {accuracy}")
##########################################################################
########
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from imblearn.metrics import specificity_score
from sklearn.metrics import accuracy_score

a=recall_score(y_test, y_pred, average='macro')
b=f1_score(y_test, y_pred, average='macro')
c=precision_score(y_test, y_pred, average='macro')
d=specificity_score(y_test, y_pred, average='macro')
e=accuracy_score(y_test, y_pred)

print("recall_score:", a)
print("precision_score:", b)
print("f1_score:", c)
print("specificity_score:", d)
print("accuracy_score:", e)
```

Results

```
Accuracy on testing set: 0.9998332777592531
recall_score: 0.9998263888888889
precision_score: 0.9998312239457303
f1_score: 0.9998361730013106
```

```
specificity_score: 0.9999441090990386
accuracy_score: 0.9998332777592531
```

III.7. CONCLUSION

In this chapter, we have performed extensive simulations to evaluate the fault diagnosis capabilities of the proposed power electronic converter system. The results obtained from these simulations provide valuable insights and demonstrate the effectiveness of our diagnostic approach with high accuracy.

GENERAL CONCLUSION

GENERAL CONCLUSION

The MMC is anticipated to be a preferred choice for medium and high-voltage power applications due to its inherent advantages, such as scalable multilevel output voltage, low harmonic content in output voltage and current, modular and flexible design, enhanced efficiency, and redundancy. As a topology oriented towards applications, it is expected that the MMC will be increasingly customized and well-adapted to specific application areas, particularlyin power transmission and quality improvement. Focusing on submodule and overall topologies, mathematical modeling and control methods, modulation techniques, and power losses, with an emphasis on the incorporation of WBG technology. Among various submodule configurations, the HBSM remains dominant in commercial use due to its simple architecture and low cost. Newly developed submodule circuits could be examined in comparative studies to balancemodule size and cost against switching losses and fault tolerance. Additionally, new advanced topologies could be explored to achieve better performance and meet diverse load requirements, especially under fluctuating or unbalanced loads.

Regarding MMC control, this review discusses the control of output voltage and current under different grid conditions, submodule balancing control, and circulating current control. Key challenges include managing submodule balancing, circulating current control, simultaneous control of multiple variables, and the resulting complexity. Nonlinear and predictive control strategies are highlighted as promising alternatives to conventional methods. Modulation techniques are reviewed and categorized by switching frequency, considering application areas and implementation efforts. Power losses are analyzed with WBG technology using various modulation methods and switching frequencies. Performance comparisons show that PSC-PWM offers better output performance but generates higher power losses compared to PD-PWM and SAM-PWM. WBG semiconductors demonstrate superior performance in reducing power losses and increasing power efficiency, particularly at high switching frequencies. Integrating WBG technology will further enhance MMC applications by offering advantages such as high-voltage and high-power operations, low power losses, high efficiency, improved reliability, and reduced module size and cooling requirements.

Finally, this review focuses on MMC topology, modeling, control, and modulation techniques for stationary applications, with future research set to explore MMC applications in vehicles.

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