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Presented by:

1. **Rebiha Moatassem Bellah**
2. **Laadjali Bachir**

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Board of Examiners:

Dr.

Chairman

Dr.

Supervisor

Dr.

Examiner

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Abstract

This dissertation presents a comprehensive review and comparative analysis of Maximum Power Point Tracking (MPPT) control strategies for photovoltaic (PV) systems operating under both constant and variable solar irradiance conditions. The study investigates four prominent algorithms: Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Networks (ANN), and Fuzzy Logic Control (FLC). The operational principles, advantages, and limitations of each technique are thoroughly examined. Using MATLAB-Simulink as a simulation platform, a quantitative performance evaluation is conducted. The results demonstrate that the ANN-based MPPT controller achieves the highest conversion efficiency, recording 96.63% under constant irradiance, while the FLC algorithm exhibits superior dynamic response characterized by minimal steady-state oscillations and rapid adaptability to fluctuating atmospheric conditions. The findings underscore the critical role of appropriate MPPT selection tailored to specific system requirements and environmental dynamics. Future research directions are proposed, focusing on experimental validation of the simulated results and the development of hybrid algorithms combining the strengths of multiple techniques to further optimize PV system performance under real-world operating conditions.

Keywords: Maximum Power Point Tracking (MPPT), Photovoltaic Systems, Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Networks (ANN), Fuzzy Logic Control (FLC), MATLAB-Simulink, Conversion Efficiency, Variable Irradiance, Hybrid MPPT Algorithms.

ملخص

تقدم هذه المذكرة دراسةً شاملةً وتحليلًا مقارناً لاستراتيجيات التحكم في تعقب نقطة القدرة القصوى (MPPT) المخصصة للأنظمة الكهروضوئية العاملة تحت ظروف إشعاع شمسي ثابت ومتغير. تبحث الدراسة في أربع خوارزميات رئيسية وهي: الاضطراب والرصد (P&O)، والتوصيلية المتزايدة (INC)، والشبكات العصبية الاصطناعية (ANN)، والتحكم المنطقي الضبابي (FLC). تم تحليل مبادئ التشغيل والمزايا والقيود لكل تقنية بدقة. باستخدام بيئة المحاكاة MATLAB-Simulink، تم إجراء تقييم كمي للأداء. أظهرت النتائج أن وحدة التحكم MPPT القائمة على الشبكات العصبية الاصطناعية (ANN) تحقق أعلى كفاءة تحويل، حيث سجلت 96.63% تحت إشعاع ثابت، في حين أظهرت خوارزمية التحكم المنطقي الضبابي (FLC) استجابة ديناميكية فائقة تميزت بتموجات (تذبذبات) ضئيلة في الحالة المستقرة وقدرة عالية على التكيف السريع مع التقلبات الجوية. تؤكد النتائج على الدور الحاسم لاختيار تقنية MPPT المناسبة وفقاً لمتطلبات النظام المحددة والظروف البيئية المحيطة. تم اقتراح اتجاهات للبحث المستقبلي، تركز على التحقق التجريبي من النتائج المحاكاة وتطوير خوارزميات هجينة تجمع بين نقاط القوة في تقنيات متعددة لزيادة تحسين أداء الأنظمة الكهروضوئية في ظل ظروف التشغيل الحقيقية.

الكلمات المفتاحية: تعقب نقطة القدرة القصوى (MPPT)، الأنظمة الكهروضوئية، خوارزمية الاضطراب والرصد (P&O)، خوارزمية التوصيلية المتزايدة (INC)، الشبكات العصبية الاصطناعية (ANN)، التحكم المنطقي الضبابي (FLC)، MATLAB-Simulink، كفاءة التحويل، الإشعاع المتغير، خوارزميات MPPT الهجينة..

DEDICATION

To those who were a light illuminating my path and a steadfast source of support, helping me overcome difficulties,

To my dear parents,

Words cannot express my gratitude, nor can phrases fully convey your rightful due.

I present to you the fruit of this effort as a token of loyalty and appreciation for all the love, support, and encouragement you have given me.

To my loyal brothers,

Companions on this journey and pillars of support, who have always stood by my side with love and sincerity,

I thank you for being in my life.

I would also like to extend my sincere thanks to my friend Bachir,

Who was an excellent friend both in academic life and beyond,

I wish him all the best and success in his journey.

Rebiha Moatassem Bellah

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
ANN	Artificial Neural Network
DC-DC	Direct Current to Direct Current
FLC	Fuzzy Logic Controller
INC	Incremental Conductance
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
P&O	Perturb and Observe
PV	Photovoltaic
PWM	Pulse Width Modulation
V_{oc}	Open Circuit Voltage
I_{sc}	Short Circuit Current

General Introduction

General Introduction

PV systems are becoming an integral part of our daily lives as the world shifts toward cleaner and more sustainable energy sources. The primary advantage of photovoltaic technology lies in its ability to convert sunlight directly into electricity, reducing our dependence on fossil fuels and mitigating environmental degradation. However, a major challenge facing these systems is their conversion efficiency, which fluctuates significantly with changing weather conditions, such as solar radiation intensity and temperature. Under low light or high temperatures, performance can drop drastically, making it difficult to rely on these systems without advanced optimization. To address this, researchers have focused on Maximum Power Point Tracking (MPPT) techniques, which are essential for ensuring that PV systems operate at their maximum potential by continuously adapting to environmental fluctuations.

The objective of this thesis is to evaluate and compare various MPPT algorithms to determine the most effective solution for different scenarios. Specifically, we analyzed and contrasted four methods: Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Networks (ANN), and Fuzzy Logic Control (FLC). Through simulations, we assessed their response speed, stability, and efficiency in tracking sudden changes in sunlight. Our findings indicate that while each method has its trade-offs—such as the simplicity of P&O versus its instability—intelligent methods like ANN demonstrated superior performance under dynamic conditions.

The project is organized into four main chapters:

Chapter I: Solar Radiation and Photovoltaic Energy

This chapter provides an overview of solar energy principles and PV system components. It explains the fundamental physics of electricity generation via the photovoltaic effect and discusses the factors affecting solar radiation.

Chapter II: MPPT Techniques for PV Systems

This technical chapter focuses on the role of DC-DC converters and the various MPPT control strategies. It categorizes these techniques into classical and intelligent methods, explaining the operating principles of each.

Chapter III: Modeling and Simulation of MPPT Algorithms

In this chapter, we present the mathematical modeling and the simulation environment used to test the four algorithms. We detail the parameters and the configurations designed to evaluate their performance.

Chapter IV: Results, Comparison, and Discussion

General Introduction

The final chapter presents the comparative results of the simulations under both static and dynamic conditions. It provides a detailed discussion on the efficiency, stability, and response time of each algorithm, concluding with a recommendation for the optimal technique

Chapter I:
Solar Radiation and
Photovoltaic Energy

I.1. Introduction :

Solar radiation represents the most abundant energy resource on Earth and serves as the fundamental primary source for photovoltaic (PV) systems. Photovoltaic energy is harnessed through specialized cells that facilitate the direct conversion of sunlight into electrical energy.

This chapter provides a comprehensive analysis of solar energy principles, explores the fundamental concepts of PV systems, and details the mechanisms of electricity generation via the photovoltaic effect. Furthermore, it examines how solar energy intensity fluctuates according to geographical location and seasonal variations.

I.1.1 Overview and Motivation

The growing global demand for electrical energy, which is largely supplied by fossil fuels such as oil and coal, has placed considerable pressure on fossil fuel reserves and has significantly affected the global environment. The limited availability of these resources, which still represent the dominant source of energy worldwide, leads to substantial emissions of greenhouse gases, including nitrous oxide (N₂O), carbon dioxide (CO₂), and methane (CH₄), which are among the major contributors to climate change (IPCC, 2007).

Furthermore, the intensive use of fossil fuels in transportation, combined with the continuous expansion of industrial activities, has resulted in serious air pollution and has intensified environmental challenges [1, 2], in order to sustain economic development while preserving natural ecosystems for future generations, it is essential to adopt alternative, sustainable, and clean energy sources, achieving these objectives requires coordinated global efforts, as highlighted in international agreements such as the Kyoto Protocol [3].

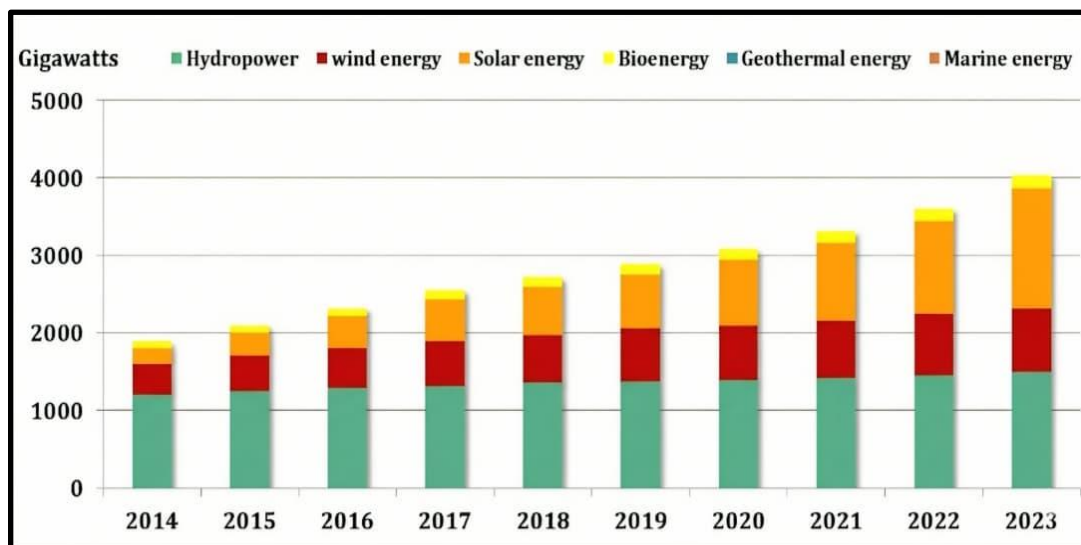


Figure I.1: Global power generating capacity [4].

Among the various renewable energy technologies, solar photovoltaic energy and wind power have witnessed remarkable expansion, surpassing other forms of renewable energy sources (RES) in terms of development and deployment, as illustrated in Figure 1.2, photovoltaic systems (PV) and wind energy account for approximately 33% and 28% of newly installed renewable energy capacity, respectively, highlighting their growing contribution to the global renewable energy portfolio. This trend demonstrates the considerable potential of these technologies to assume a leading role in the decarbonization of the energy sector. Furthermore, the geographical potential for solar energy exhibits significant regional variability, as presented in Figure 1.3.

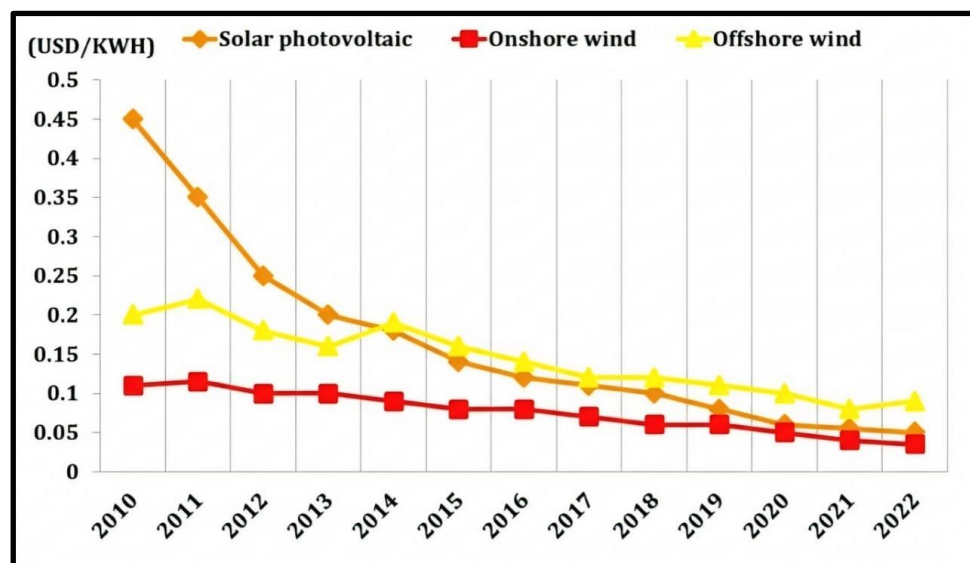


Figure I.2: Levelised cost of electricity from newly commissioned solar PV, onshore wind power and offshore wind power, 2010-2022 [5].

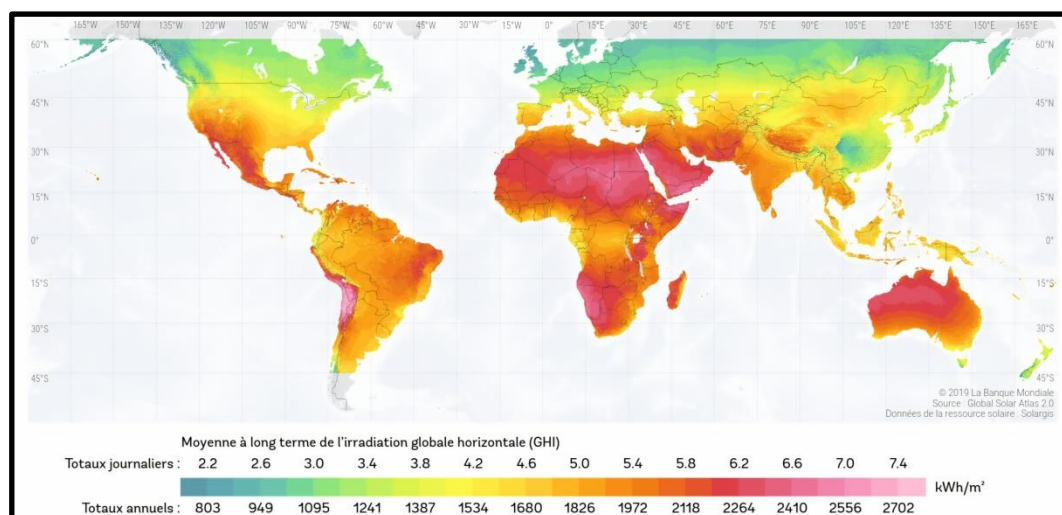


Figure I.3: Solar irradiation map of the world from photovoltaic guidenr

The levelized cost of electricity (LCOE) associated with renewable energy technologies has undergone a substantial decline in recent years, among these, onshore wind energy has demonstrated the most pronounced reduction, with the global average LCOE

decreasing by approximately 50% between 2010 and 2022, reaching USD 0.033 per kilowatt-hour (kWh), similarly, solar photovoltaic (PV) systems have experienced a significant cost decrease, with the global average LCOE reported at USD 0.049 per kWh in 2022, in contrast, offshore wind energy remains relatively more expensive, with an LCOE of USD 0.081 per kWh (refer to Figure I.2).

Despite these improvements in cost-efficiency, the integration of renewable energy sources, particularly solar PV, into electrical grids poses considerable challenges due to their intermittent nature, the direct current (DC) voltage output of these systems is inherently variable and influenced by fluctuating environmental conditions, which renders direct grid connection impractical, this issue has prompted significant advancements in power electronic converters (PECs) as a critical technological solution.

Power electronic converters act as intermediary devices between renewable energy systems and the electrical grid, these converters mitigate the variability of output voltage by dynamically regulating it, thereby ensuring efficient power conversion and maintaining balanced power distribution, through these mechanisms, PECs enhance grid compatibility and facilitate the reliable delivery of electricity generated from renewable sources.

I.1.2 Power Electronics Converters for Renewable Energy System

Power electronic converters (PECs) play a pivotal role in enabling the integration of renewable energy sources (RES) with electrical grids or load systems, as their operation directly influences overall system performance, including stability, reliability, efficiency, power quality, and consumption ratios. To achieve energy conversion processes that are both cost-effective and efficient, various innovative PEC systems are being developed in parallel with the increasing practical deployment of renewable energy technologies [4], Figure 1.4 illustrates a comprehensive framework for integrating RES through the application of PECs.

The integration of RES into electrical systems necessitates the use of PECs to align the variable outputs of renewable sources with the operational requirements of the power grid, consequently driving substantial advancements in PEC efficiency, these improvements are primarily realized through two approaches: (a) the development of novel power converter architectures or (b) the implementation of advanced control strategies, both of which enhance the capability of PECs to facilitate reliable and efficient energy delivery from renewable sources.

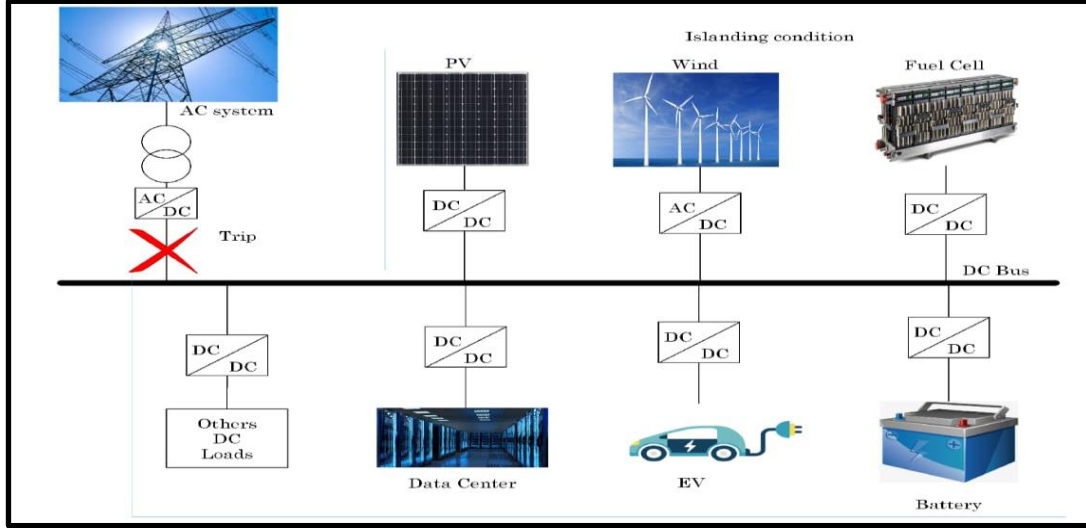


Figure I.4: Schematic exhibiting the relationship of a RES to the electricity grid.

The classification of converters within renewable energy systems (RES) includes two main categories: galvanically isolated and non-isolated variants [6], [7], galvanically isolated converters, also referred to as transformer-based converters, utilize a transformer to provide input-output isolation, as emphasized in the topological analyses of [8], [9], [10], this isolation mechanism enhances their operational capabilities. However, the integration of transformers introduces several challenges, including higher financial costs, larger physical size, and reduced efficiency, these limitations are not present in non-isolated, transformer-less solutions, as confirmed by empirical evidence from various case studies [11], [12]

Consequently, when all critical factors are taken into account, non-isolated converters are generally considered a more advantageous option for power conversion processes within renewable energy applications.

I.1.3 Review of PV Energy System Applications

Photovoltaic (PV) energy conversion systems play a fundamental role in integrating renewable energy into the utility grid, offering a sustainable and efficient solution for electricity generation, Figure 1.5 illustrates the structural configuration of such a system, starting with PV arrays that capture solar irradiance and convert it into direct current (DC) electrical energy, which is subsequently stabilized through DC bus structures. A multilevel power electronic converter constitutes the central component, enabling the conversion of DC power into alternating current (AC) power with high quality and reduced Total Harmonic Distortion (THD), a filtering stage ensures

compliance with grid standards by attenuating high-frequency noise, while an optional transformer may be included to perform voltage adaptation and provide electrical isolation between the PV system and the grid.

The control unit, incorporating a Maximum Power Point Tracking (MPPT) controller, guarantees optimal energy extraction from the PV arrays and precise regulation of the power electronic converter, ultimately allowing the AC power to be injected into the utility grid, thereby demonstrating an advanced integration of sophisticated control algorithms and power conversion technologies for efficient solar energy utilization and enhanced grid compatibility.

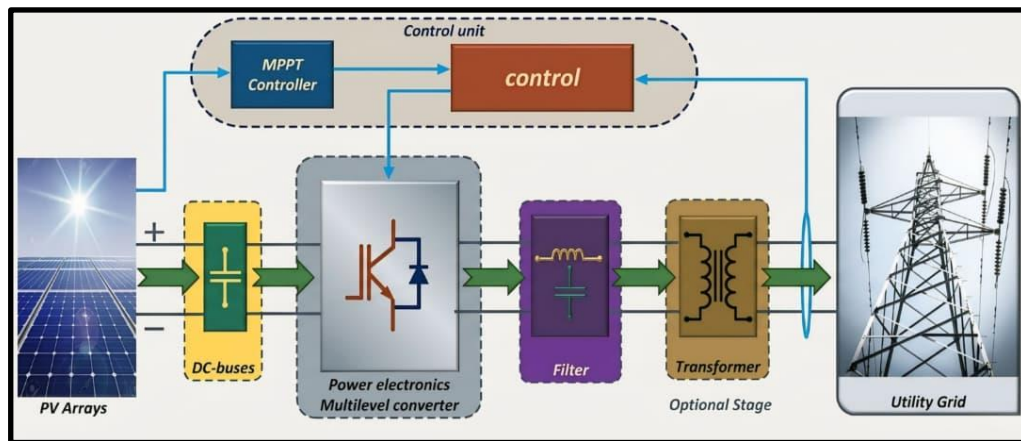


Figure I.5: A photovoltaic (PV) system with power electronics and the needed control.

I.1.4 Classification of power converters

Power electronic converters have been widely employed in numerous industrial applications to achieve efficient power conversion and enhance energy conservation, depending on the type of electric power conversion and the direction of power flow, power converters can be classified into four main categories:

- **AC-DC rectifiers:** These devices convert single-phase or three-phase AC voltage into DC, and are commonly used as front-end converters in variable-speed motor drives and wind energy conversion systems.
- **DC-DC converters:** These converters transform a DC voltage from one level and polarity to another level, and in certain applications, to a different polarity.
- **DC-AC inverters:** These inverters convert DC into variable-voltage and variable-frequency AC for variable-speed motor drives, while conversion from unregulated or regulated DC to fixed AC is applied in grid-connected renewable energy systems.

- AC-AC cycloconverters: These devices convert an AC voltage of a specific level, frequency, and number of phases into an AC voltage of a different level, frequency, and, in some cases, a different number of phases.

I.1.5 Classification of DC–DC converters

Numerous researchers have investigated different types of DC–DC converters for renewable energy applications and energy storage, aiming to enhance efficiency while addressing the inherent limitations of conventional converters, DC–DC converters can be classified into three main operational modes, as illustrated in Figure 2 [13–15], namely linear mode, hard switching mode, and soft switching mode. The linear mode is characterized by simplicity, low noise, good voltage regulation, and fast response, however, its main limitation is low efficiency due to power losses under various operating conditions.

Hard switching mode converters can be further divided into non-isolated and isolated types based on the presence of galvanic isolation, typical examples of non-isolated hard switching topologies include buck, boost, buck–boost, and Cuk converters, which are commonly referred to as chopper circuits, conversely, galvanic isolation through a transformer is required for safety purposes when converters are supplied by the utility grid.

Power converters, together with their associated control strategies, are employed to regulate node voltages in microgrids with various types of loads, including resistive, inductive, nonlinear, constant power, or critical loads, however, constant power loads (CPLs) have a significant impact on the stability of converter output voltages and are generally challenging to regulate using conventional control techniques [16, 17].

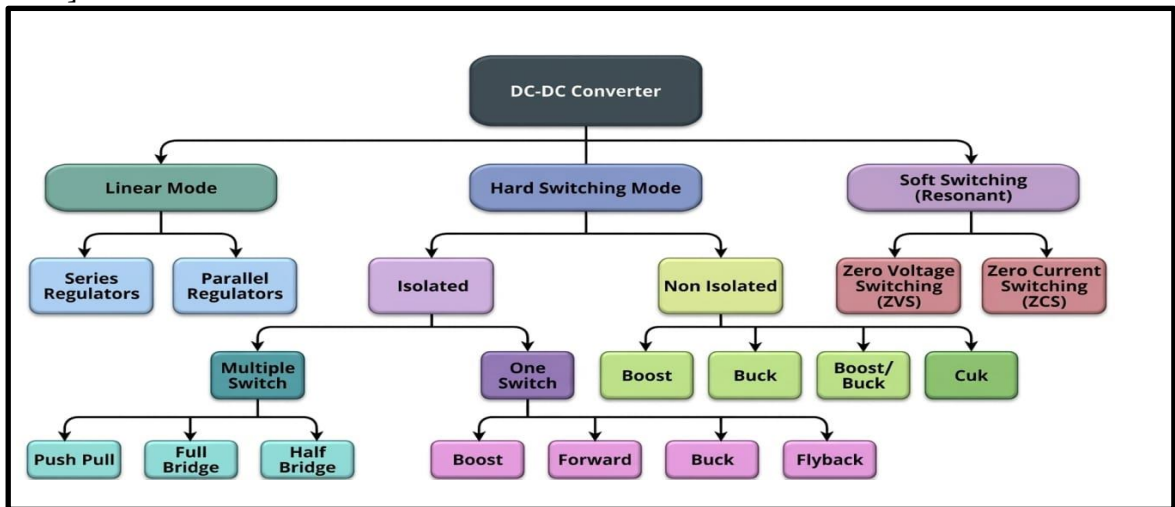


Figure I.6: Classification of DC–DC converters [18].

I.2. Solar Radiation :

Solar radiation is defined as the entirety of the radiative emissions originating from the Sun. In addition to cosmic particles characterized by extremely high velocities and energy levels, the Sun emits electromagnetic waves spanning a broad spectrum from radio waves to gamma rays, including the visible light region.

The emission of these electromagnetic waves is accurately modeled as a black body at a temperature of 5800 Kelvin, in accordance with Planck's Law. The spectral emission peak occurs within the yellow spectrum at a wavelength of approximately $\lambda=570$ nm. This radiation is distributed nearly equally between visible light and infrared radiation, while ultraviolet radiation accounts for approximately 1% of the total emission.

Upon traversing the Earth's atmosphere to reach sea level, solar radiation undergoes several attenuation and 'filtering' processes. These effects are distinctly observable in the spectrum through absorption bands attributed to atmospheric constituents, most notably the ozone layer which absorbs a significant portion of ultraviolet radiation as well as oxygen, carbon dioxide, and water vapor [1].

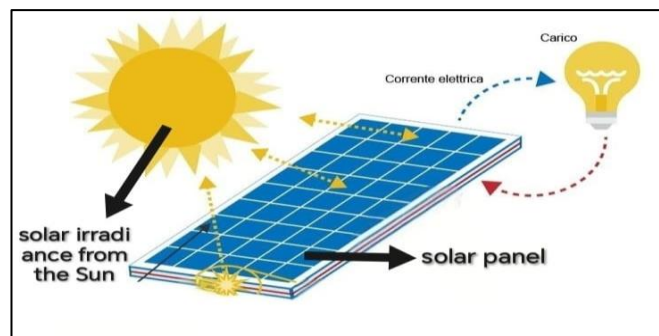


Figure 1.7: Representation of Solar Radiation

I.2.1. Radiation Spectrum:

As solar radiation traverses the Earth's atmosphere to reach sea level, it undergoes various "filtering" and attenuation processes. Specific atmospheric constituents, such as the ozone layer (which absorbs a significant portion of UV radiation), oxygen, carbon dioxide, and water vapor, create distinct absorption bands within the spectrum

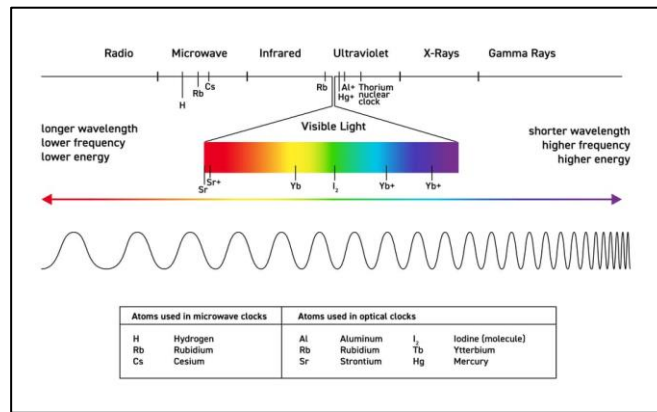


Figure 1.8: Solar Radiation Spectrum

Radiant Energy Bandwidth: Approximately 99.8% of the Sun's radiant energy is concentrated within a narrow spectral range from 20 to 2500 nanometer [2].

Surface Composition: Upon reaching the surface, the composition of solar energy is approximately 5% ultraviolet, 42% visible light, and 53% near-infrared radiation.

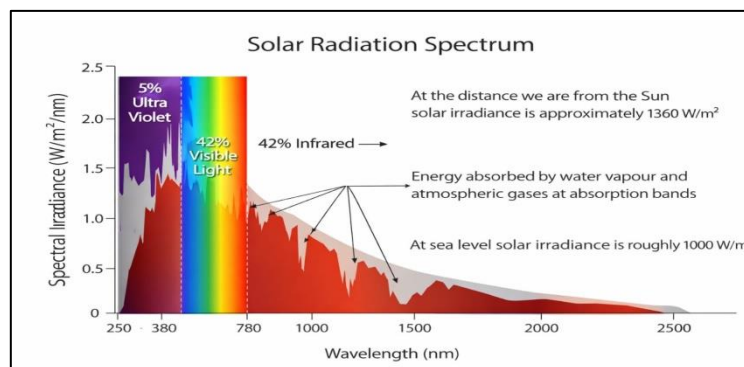


Figure 1.9: Representation of Solar Radiation Spectrum

I.3. Conversion of Solar Radiation by PV Effect:

A photovoltaic cell is composed of two semiconductor layers (typically silicon) that are chemically doped to create a specific polarity:

P-Layer (Positive): Incorporated with boron atoms to establish a positive charge.

N-Layer (Negative): Incorporated with phosphorus atoms to establish a negative charge.

Mechanism: This configuration establishes a potential barrier at the junction. When photons with sufficient energy are absorbed by the semiconductor, they liberate electrons from their valence bonds, creating "hole" pairs.

The resulting potential difference between these layers, known as the photovoltaic effect, drives an electric current when an external circuit is connected [1].

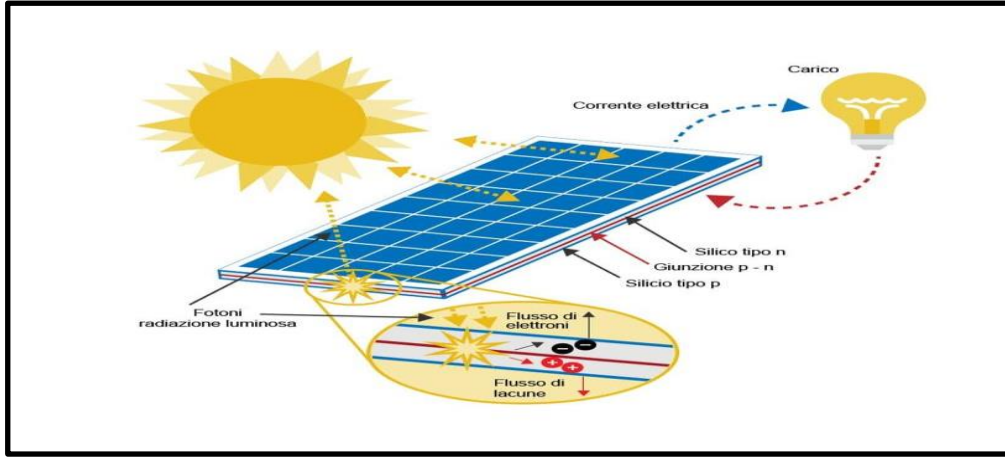


Figure 1.10: Solar Radiation Conversion by PV Effect

I.4. Photovoltaic Generator:

The photovoltaic sensor is defined by its electrical behavior, which is primarily described by the current–voltage relationship $i=f(v)$, as shown in Figure (1.5). This model is widely employed to predict the electrical output of the sensor, namely the voltage and current, as a function of two main input parameters: the operating temperature and the level of incident solar irradiation.

At a given voltage, the current generated by a photovoltaic module depends solely on the illumination intensity and the cell temperature. When these two parameters remain constant, the performance of the solar cell is governed by the electrical load connected to the circuit. Under open-circuit conditions ($R_c = \infty$, $I = 0$, $V = V_{oc}$) or a short circuit ($R_c = 0$, $I = I_{cc}$, $V = 0$), no electrical energy is delivered to the external load. Between these two limiting cases, there exists an optimal load resistance **R_{opt}** for which the output power of the solar cell reaches its maximum value.

This maximum power is given by ($P = V_{max} \times I_{max}$) provided by the solar cell to the load resistance is maximal, thus reaching P_{max} [2].

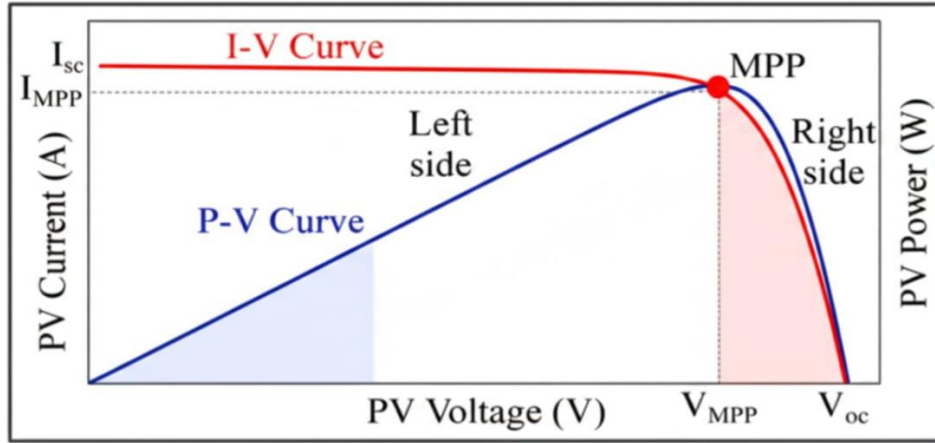


Figure 1.11: Typical Characteristics of a PV Generator

The energy conversion efficiency of a solar cell is defined as $\mu_{max} = \frac{P_{max}}{P_{\gamma}}$ $\mu = \frac{P}{P_{\gamma}}$

In practice, an increase in temperature leads to a reduction in photovoltaic efficiency. This limitation has motivated the development of hybrid systems that combine photovoltaic cells with thermal collectors. Such hybrid sensors enable the simultaneous production of electrical energy and hot water, while enhancing photovoltaic performance through effective cell cooling.

Finally, the electrical power delivered by the solar cell ($P = I \times V$) and its overall efficiency are strongly influenced by several factors, including the semiconductor material and fabrication technology (amorphous silicon, polycrystalline silicon, monocrystalline silicon), the junction structure and geometry (layer thickness, multilayer configurations), as well as external operating conditions such as temperature, spectral composition and intensity of incident radiation, and the characteristics of the external electrical load connected to the cell .



Figure 1.12: Block Diagram of a PV Generator

I.4.1. Photovoltaic Cell:

Photovoltaic modules are composed of an assembly of interconnected solar cells. These cells are embedded in resin and encapsulated either between two panes of tempered glass, forming double-glass modules, or between a tempered glass pane and a Tedlar backsheet, resulting in glass/Tedlar modules. In most cases, this assembly is mounted within an anodized aluminium frame; however, frameless configurations are also available, particularly for building-integrated photovoltaic applications, where aluminium profiles are used for installation on façades or rooftops.

The electrical power delivered by a photovoltaic module is primarily determined by its active surface area and the level of incident solar irradiation. This power is conventionally expressed in peak watts (Wp), corresponding to the maximum power output of the module under standard test conditions, with a reference solar irradiance of 1000 W/m².

The output voltage of a photovoltaic module depends on the number of solar cells connected in series. For low-power modules (less than 75 Wp), the nominal operating voltage typically ranges between 12 and 15 volts. Modules with higher power ratings are achieved by increasing the number of cells connected in series, which leads to a higher output voltage, and by increasing the number of parallel cell strings, which results in a higher output current. Consequently, the operating voltage may reach 24 volts or more, depending on the configuration of the system to be supplied.

The surface area of photovoltaic modules varies according to the manufacturer and generally lies between 0.5 and 1 m², while it may reach up to 3 m² for special designs or large-scale productions. Several interconnected modules constitute a photovoltaic panel, and multiple interconnected panels form a photovoltaic array. By arranging modules in series and/or in parallel, a wide range of output voltages and power levels can be obtained [1].

I.4.2. Modelling of a PV Cell:

The operation of a photovoltaic module is commonly represented by the standard one-diode model, originally developed by Shockley for a single photovoltaic cell and subsequently extended to photovoltaic modules by modeling them as assemblies of identical cells interconnected in series and/or in parallel

In the scientific literature, a photovoltaic cell is frequently modeled as an electrical current generator whose behavior is equivalent to a current source connected in parallel with a diode. In order to account for the physical phenomena occurring at the cell level, this basic model is augmented by the inclusion of two resistive elements: a series resistance R_s and a shunt resistance R_{sh} , as depicted in the equivalent electrical circuit shown in Figure (1.7)

The series resistance represents the internal resistance of the photovoltaic cell and is mainly determined by the resistive properties of the semiconductor material, the contact resistance associated with the current-collecting grids, and the resistivity of these grids. The shunt resistance arises from leakage currents at the junction and is strongly influenced by the manufacturing quality and the technological process used in cell fabrication .

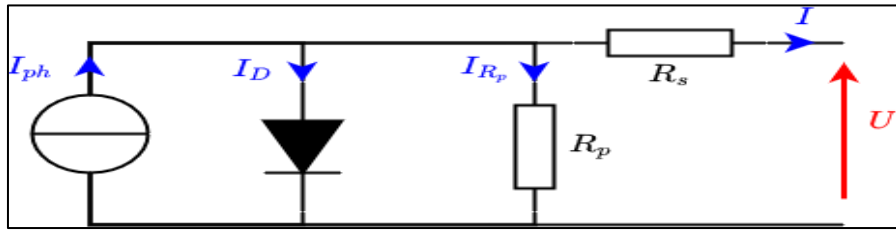


Figure 1.13: Equivalent Circuit of a PV Cell

I.4.3. Types of Photovoltaic Cells :

Photovoltaic solar panels are composed of photovoltaic cells, which can be classified into several types according to their material and manufacturing process.

1.4.3.1 Monocrystalline Cells: Monocrystalline silicon is obtained through the controlled cooling and solidification of molten silicon, resulting in a single, homogeneous crystal structure. This crystal is subsequently sliced into thin wafers that are used to fabricate photovoltaic cells. The resulting material is characterized by a uniform blue coloration, with no visible crystal boundaries or impurities



Figure 1.14: Monocrystalline Cells

1.4.3.2 Polycrystalline Cells: Polycrystalline silicon is produced by melting silicon and casting it into a square or elongated metallic mold, known as an ingot. During the solidification process, multiple silicon crystals are formed, giving rise to a heterogeneous crystalline structure. This type of photovoltaic cell is characterized by a blue coloration with visible speckled patterns resulting from the presence of crystal grains, a feature that allows for its easy identification .



Figure 1.15: Polycrystalline Cells

1.4.3.3 Hydrogenated Amorphous Cells: Amorphous silicon is produced from silicon gas, which is vapor-deposited onto a substrate such as glass, flexible plastic, or metal using a vacuum deposition technique. These photovoltaic cells are characterized by a dark gray coloration.

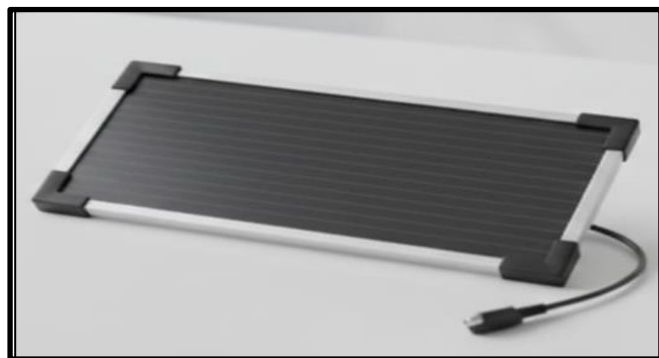


Figure 1.16: Hydrogenated Amorphous Cells

I.5. The Impact of Temperature on Solar Panel:

Temperature exerts a considerable influence on the performance of solar panels, affecting their efficiency, voltage, power output, and long-term durability:

- **Reduction in Efficiency:** As the temperature of a solar panel increases, its conversion efficiency decreases. Solar panels generate electricity by converting incident sunlight into electrical energy, and elevated temperatures reduce the effectiveness of this process.
- **Voltage Decrease:** The output voltage of a solar panel declines with rising temperature. This phenomenon occurs because the semiconductor material within the panel becomes less effective at transporting charge carriers under higher thermal conditions.
- **Power Output Reduction:** Elevated temperatures can lead to a decrease in the overall power output of the solar panel, as the combined effects of reduced efficiency and lower voltage directly diminish generated power.
- **Thermal Degradation:** Prolonged exposure to high temperatures may cause thermal degradation of the materials composing the solar panel, ultimately reducing both lifespan and operational efficiency.
- **Operating Temperature Range:** Solar panels are engineered to function optimally within a specific temperature range. Exceeding this range can further compromise performance and reliability.

Overall, while solar panels still generate electricity on hot days, their efficiency decreases as temperatures rise, impacting their overall performance and output.

I.6. Advantages and Disadvantages of PV Energy:

I.6.1. Advantages:

- **Renewable Energy:** Solar energy is an abundant and widely accessible renewable resource globally, making it a sustainable long-term energy source.
- **Low Greenhouse Gas Emissions:** The use of solar energy does not generate greenhouse gases, contributing to the reduction of carbon emissions and the mitigation of climate change.
- **Decreasing Costs:** The cost of solar technologies has significantly declined over recent years, enhancing the competitiveness of solar energy compared to conventional energy sources.

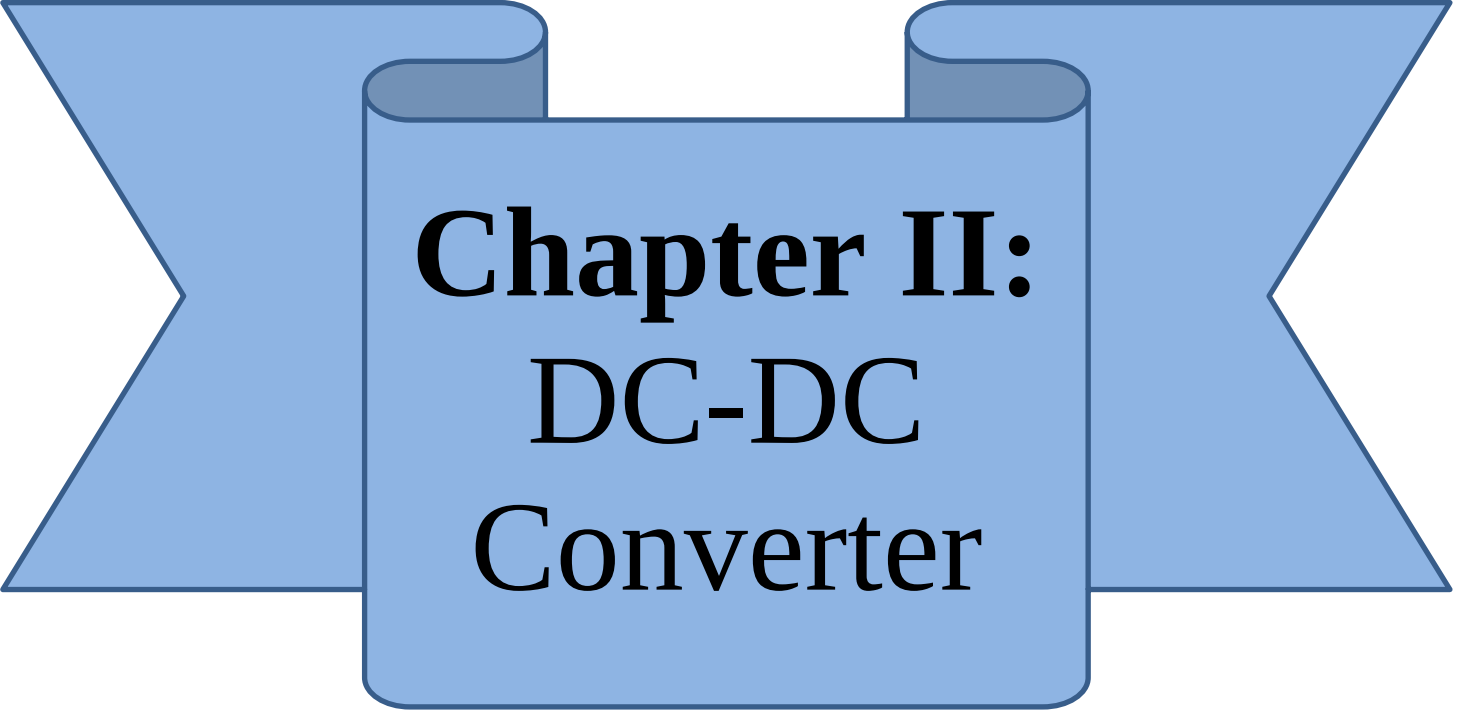
- **Energy Independence:** Photovoltaic systems enable users to generate their own electricity, reducing reliance on external energy suppliers and minimizing exposure to market price fluctuations.
- **Low Maintenance:** Once installed, solar energy systems require minimal maintenance, thereby lowering long-term operational costs.

I.6.2. Disadvantages:

- **Sunlight Variability:** Solar energy generation depends on sunlight availability, resulting in variable and intermittent electricity production that often necessitates energy storage solutions or integration with other energy sources.
- **High Initial Costs:** Despite the reduction in solar technology costs, the initial investment required for solar installations can remain relatively high .
- **Environmental Impact:** Although solar energy is generally considered clean, the manufacturing and disposal processes of solar panels may have environmental consequences.
- **Space Requirement:** Solar installations often demand large land or roof areas to accommodate panels, which can be challenging in densely populated urban regions or locations with limited space.
- **Dependency on Weather Conditions:** The performance of solar systems is influenced by weather conditions, such as clouds, rain, or snow, which can reduce the efficiency of electricity production at specific times.

I.7. Conclusion:

In conclusion, this chapter has addressed the fundamental principles of solar radiation and the conversion of solar energy into electricity through photovoltaic systems. It has explained how solar cells utilize the photovoltaic effect to produce electrical energy from sunlight. The chapter also discussed the modeling and characteristics of photovoltaic generators, including factors that affect their efficiency, such as temperature and load resistance. Various types of photovoltaic cells, categorized according to the silicon crystal structure, were presented. Additionally, the chapter reviewed the main components of photovoltaic modules and highlighted the primary advantages and disadvantages associated with solar photovoltaic technology.



Chapter II: DC-DC Converter

II.1.Introduction :

Direct Current (DC-DC) converters represent fundamental components within contemporary power management architectures. Their primary utility lies in the efficient transformation of DC voltage levels, facilitating a regulated and stable power supply to diverse electronic subsystems.

In environments characterized by input voltage instability such as the progressive discharge of electrochemical batteries or dynamic load variations these converters act as precision regulators to maintain a constant output voltage, This stability is crucial for the operational integrity of sensitive electronic components.

A definitive technical advantage of DC-DC converters is their high conversion efficiency, Unlike linear regulators or resistive-based systems that dissipate significant energy as heat, DC-DC converters utilize High-Frequency Switching techniques to minimize power loss, This optimization not only enhances system thermal management but also significantly extends the operational lifespan of portable, battery-operated devices.

Furthermore, these converters provide essential functionalities such as voltage stepping (Buck/Boost) and galvanic isolation, which mitigates ground loop interference and shields delicate circuitry from transient voltage spikes and electromagnetic noise.

II.2.DC-DC Converters :

DC-DC converters (also known as power choppers) are static power electronic systems designed to transform a fixed DC input into a controllable and adjustable DC output voltage across a specified load.

Depending on the power requirements and switching frequency, these converters are generally classified into two technological categories:

Thyristor-based Converters: Utilized for high-power industrial applications (reaching several hundred Megawatts), Due to the inherent characteristics of thyristors, these systems typically operate at lower chopping frequencies, often in the range of a few kilohertz (kHz).

Transistor-based Converters: Employed for low to medium power applications (up to approximately 100 kW), The use of power transistors (such as MOSFETs or IGBTs) allows for significantly higher chopping frequencies, reaching up to 100 kHz, which facilitates the use of smaller inductive and capacitive filtering components.

Note: The symbol illustrated below represents the standard schematic notation for a DC-DC converter in power electronics diagrams.

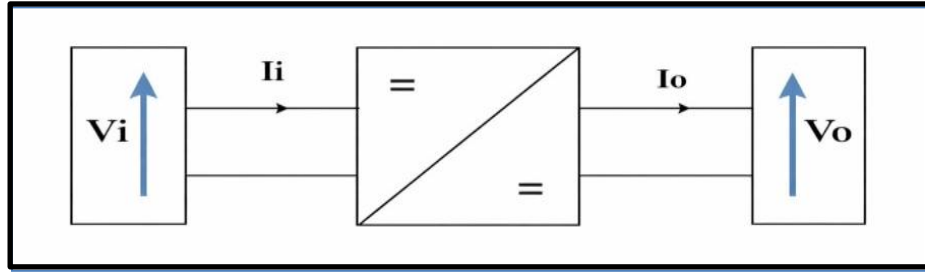


Figure II.1: DC-DC Converters

II.3.Applications of DC-DC Converter :

For several decades, switch-mode power converters have been extensively integrated into modern electronic systems across diverse sectors, including industrial, commercial, utility, and consumer markets.

In low-power DC-DC conversion, the prevailing architectural standards are primarily based on three fundamental topologies: buck, boost, and buck-boost converters. However, specialized technical requirements often demand advanced configurations or modified variations of these conventional designs to optimize performance.

The scientific literature documents numerous DC-DC converter topologies; however, a universal solution for all possible applications remains non-existent, In a broader context, these conversion techniques have become indispensable across industrial processes, research and development initiatives, and daily technological interactions [4].

DC-DC converters represent a pivotal area of research within power electronics and energy drives, owing to their widespread implementation in various industrial frameworks, A selection of these applications is depicted in Figure (II.2).

Specifically, high-voltage gain converters are essential for sophisticated systems, including radar technology, DC distribution networks, data centers, and the extraction of energy from renewable sources [5].

This functionality is particularly critical in renewable energy sectors, where high-voltage gain DC-DC converters are employed to elevate low-magnitude source voltages

to levels compatible with distribution grids, Generally, DC distribution paradigms offer systemic advantages, such as a reduction in conversion stages, cost-efficiency, and enhanced power quality, establishing them as a preferred choice for a broad spectrum of contemporary applications.



Figure II.2: Applications of DC/DC Converters.

Here are some of DC-DC converter applications:

- Renewable energy applications:** The integration of DC-DC converters in renewable energy systems necessitates the extraction of a continuous and stabilized input current to achieve significant ripple reduction. These converters must demonstrate high compatibility for integration with heterogeneous power sources. Typically, non-isolated interleaved high voltage gain topologies are utilized as the primary interface between renewable sources and microgrids to ensure optimal power flow and system stability[6].
- Medical devices:** In medical instrumentation, isolated DC-DC converters are indispensable for applications where galvanic isolation is a critical safety requirement, effectively decoupling the output stage from hazardous input voltages. Conversely, non-isolated converter configurations are appropriately implemented in specific subsystems, such as the power supply units for X-ray imaging systems, where direct isolation may not be the primary design constraint.
- Vehicles :** In automotive engineering, the primary DC-DC converter transforms energy from the high-voltage onboard traction battery into lower DC voltage

levels required to power auxiliary systems, including lighting, wipers, and window control mechanisms [7], This architecture is standard in both electric vehicles (EVs) and hybrid electric vehicles (HEVs), Galvanic isolation is mandatory when control systems must be decoupled from high-voltage domains, Furthermore, Buck-boost converters are employed for bidirectional voltage regulation, while charge-pump converters are utilized for voltage inversion tasks

- **Smart lighting:** Advanced lighting applications necessitate LED backlight driver solutions characterized by high efficiency, precise direct current regulation, over-voltage protection, and PWM-based control within a streamlined design.

The DC-DC converter types effectively serving as drivers in this sector include linear regulators, charge pumps, and conventional switching converters.

II.4.Types of DC-DC converters :

There are three types of DC-DC converters, namely: Buck, Boost, and Buck-Boost.

II.4.1.Buck Converter :

Buck Converter is a type of DC-DC converter that is designed to perform step-down conversion of the applied dc input signal. In the case of buck converters, the fixed dc input signal is changed into another dc signal at the output which is of lower value. This means it is designed to produce a dc signal as its output that possesses a lower magnitude than the applied input. It is sometimes called Step-down DC to DC Converter or Step-down Chopper or Buck Regulator.

II.4.1.1.Operating Principle of Buck Converter :

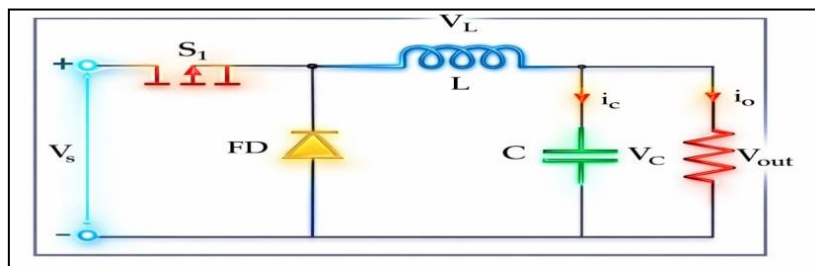


Figure II.3: The Circuit Representation of Buck Converter

In the above figure, it is clearly shown that along with the power electronics solid-state device which acts as a switch for the circuit, there is another switch in the circuit which is a freewheeling diode. The combination of these two switches forms a connection with a low-pass LC filter in order to reduce current or voltage ripples. This helps in generating regulated dc output. A pure resistor is connected across this whole arrangement that acts as a load of the circuit.

The whole operation of the circuit takes place in two modes. The first mode is the one when the power MOSFET i.e., switch S_1 is closed.

In this mode of operation, switch S_1 is in closed condition thus allows the flow of current to take place through it.

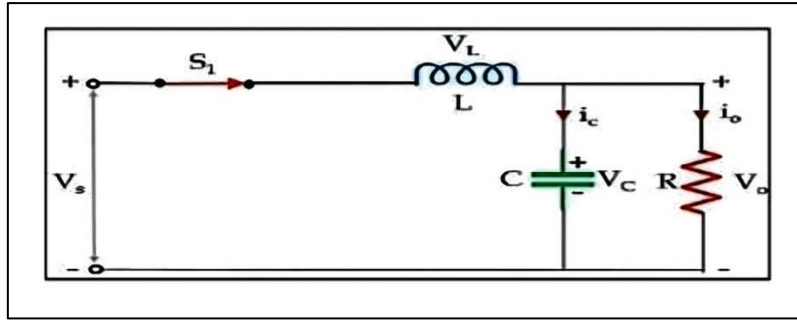


Figure II.4: Buck Converter When S_1 is Closed

Initially when a fixed dc voltage is applied across the input terminal of the circuit then in the closed condition of switch S_1 current flows in the circuit in the manner shown above. Due to this flowing current, the inductor in the path stores energy in the form of a magnetic field. Also, there is a capacitor in the circuit and current flows through it also, therefore, it will store the charge and the voltage across it will appear across the load.

However, due to Lenz's law, the energy stored within the inductor will oppose the cause which has produced it and so an induced current will get generated and the polarity across the inductor will get reversed.

Here the total time period is a combination of T_{on} and T_{off} time.

$$T = T_{on} + T_{off} \quad (II. 1)$$

The duty cycle is written as:

$$D = \frac{T_{on}}{T} \quad (II. 2)$$

On applying KVL, in the above-given circuit

$$V_s = V_L + V_{out} \quad (II. 3)$$

$$V_L = V_s - V_{out} \quad (II. 4)$$

Also,

$$V_L = L \frac{di_L}{dt} = V_s - V_{out} \quad (II. 5)$$

$$\frac{di_L}{dt} = \frac{V_s - V_{out}}{L} \quad (II. 6)$$

When S1 is in closed condition then $T_{on} = DT$ thus $\Delta t = DT$. Therefore, we can write

$$\frac{\Delta i_L}{\Delta t} = \frac{V_s - V_{out}}{L} \quad (II. 7)$$

$$\frac{\Delta i_L}{DT} = \frac{V_s - V_{out}}{L} \quad (II. 8)$$

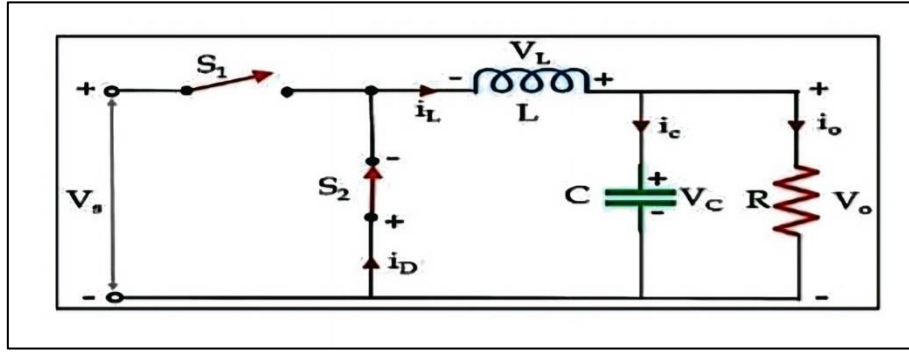
Hence,

$$\Delta i_t = \left(\frac{V_s - V_{out}}{L} \right) DT \quad (II. 9)$$

The above equation represents the change in current through the circuit when switch S1 is closed.

Now, the second mode of operation takes place when switch S₂ is closed and S₁ gets open. However, you must be thinking about how automatically, the switch S₂ will be closed. So, as we have discussed that the inductor in the circuit will store the energy so, once S₁ will get open the inductor in the circuit will start acting as the source. In this mode, the inductor releases the energy which is stored in the previous mode of operation. As we have discussed that the polarity of the inductor will get reversed therefore this causes the freewheeling diode to come in a forward-biased state which was earlier present in a reverse-biased state due to the applied dc input.

Due to this, the flow of current takes place in a way as shown below:

Figure II.5: Buck Converter When S_2 is Closed

This flow of current will take place till the time the stored energy within the inductor gets completely collapsed. As once the inductor gets completely discharged, the diode comes in reverse biased condition leading to cause opening of switch S_2 , and instantly switch S_1 will get closed and the cycle continues.

Now, let us apply KVL, in the above circuit

$$0 = V_L + V_{out} \quad (II. 10)$$

$$V_L = L \frac{di_L}{dt} = -V_{out} \quad (II. 11)$$

Since, we know,

$$T = T_{on} + T_{off} \quad (II. 12)$$

$$T = DT + T_{off} \quad (II. 13)$$

$$T_{off} = T - DT \quad (II. 14)$$

$$T_{off} = (1 - D)T \quad (II. 15)$$

$$V_L = L \frac{\Delta i_L}{\Delta t} = -V_{out} \quad (II. 16)$$

$$T_{off} = \Delta t = (1 - D)T \quad (II. 17)$$

$$L \frac{\Delta i_L}{(1 - D)T} = -V_{out} \quad (II. 18)$$

So,

$$\Delta i_L = -\frac{V_{out}}{L} (1 - D)T \quad (II. 19)$$

This equation represents the rate of change in current through the inductor when the switch S1 is open.

As we know that the net change of current through the inductor in one complete cycle is zero. Thus,

$$\Delta i_{L(s1-closed)} + \Delta i_{L(s1-open)} = 0 \quad (\text{II. 20})$$

$$\frac{V_s - V_{out}}{L} DT + \left\{ -\frac{V_{out}}{L} (1 - D)T \right\} = 0 \quad (\text{II. 21})$$

On simplifying,

$$\frac{V_s DT}{L} - \frac{V_{out} DT}{L} - \frac{V_{out} T}{L} + \frac{V_{out} DT}{L} = 0 \quad (\text{II. 22})$$

$$\left(\frac{V_s DT}{L} \right) = \frac{V_{out} T}{L} \quad (\text{II. 23})$$

$$V_{out} = DV_s \quad (\text{II. 24})$$

The figure given below represents the waveform representation of Buck Converter:

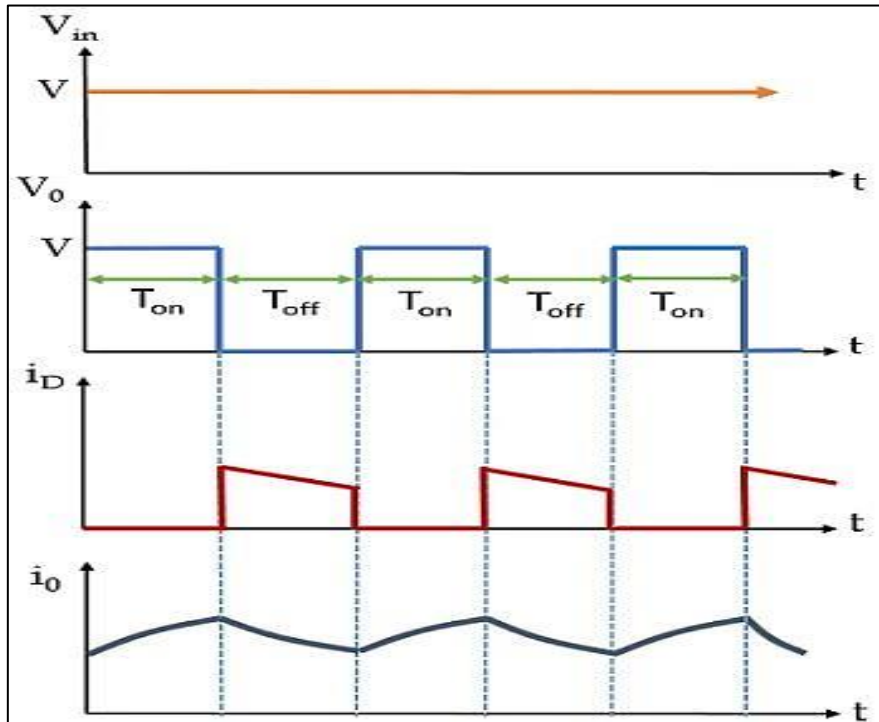


Figure II.6: Waveform Representation

Hence, we can say, buck converters are used to provide a lower value of dc signal from a fixed dc input.

II.4.2.Boost Converter :

Boost Converters sometimes, also known as step-up DC-DC converters are the type of chopper circuits that provides such an output voltage that is more than the supplied input voltage. In the case of boost converters, the dc to dc conversion takes place in a way that the circuit provides a high magnitude of output voltage than the magnitude of the supply input. It is given the name 'boost' because the obtained output voltage is higher than the input voltage.

II.4.2.1.Operating Principle of Boost Converter :

The figure given below is the circuit representation of the boost converter:

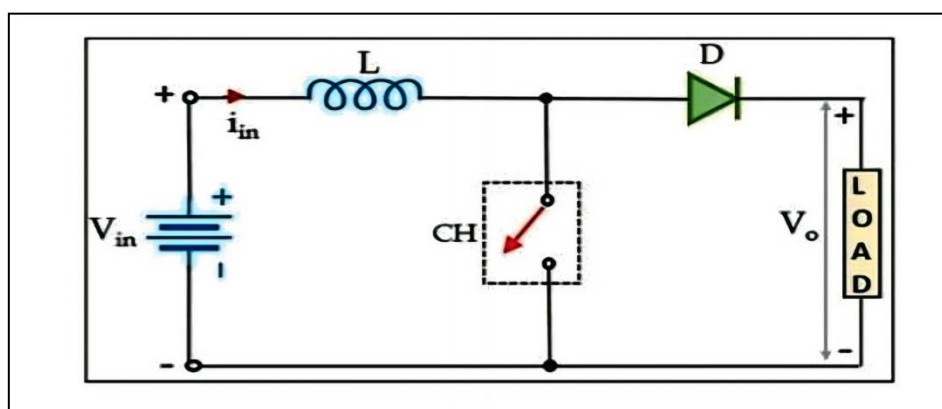


Figure II.7: Elementary Circuit of Boost Converter

The circuit here is an elementary form of step-up DC-DC converter which necessarily requires a large inductor L in series connection with the voltage source. The whole circuit arrangement operates in a way that it helps in maintaining a regulated dc signal at the output.

Let us understand how the given circuit operates in order to provide an increased dc signal at the load.

Initially, when the chopper CH is in on state, then in the presence of supply dc input current begins to flow through the closed path of the circuit i.e., passing through the inductor as shown in the figure below.

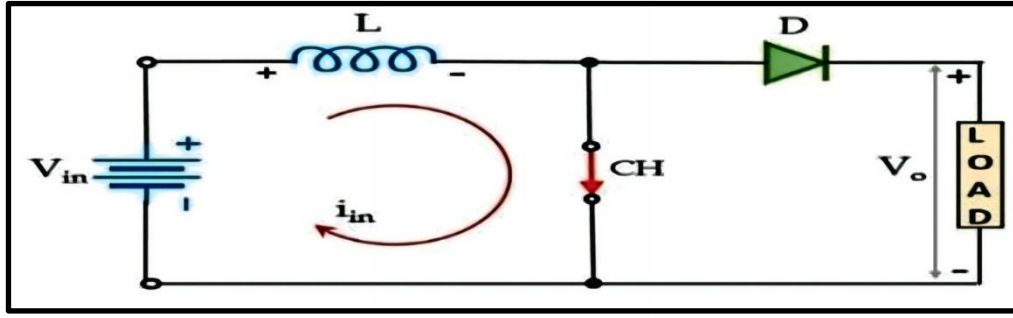


Figure II.8: The Chopper CH is in on State

Here, the polarity of the inductor will be according to the direction of the flow of current. In this particular case, the diode in the configuration is in reverse biased condition and so current will not be allowed to flow through that particular part of the circuit during on state of the DC-DC converter. Resultantly, the voltage across DC-DC converter will appear across the load.

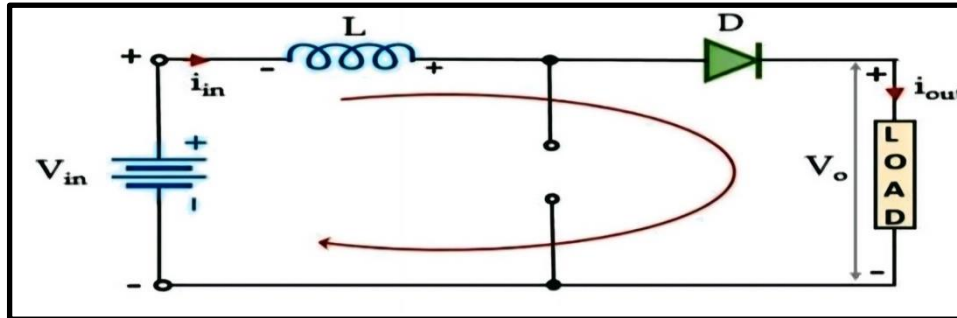


Figure II.9: The Chopper CH is in Off State

Furthermore, at the instant when CH is in the off state, then the part of the circuit through which the current was flowing earlier will not be active in this case. However, as the inductor stores, the energy in the form of a magnetic field and so the current through it will not die out instantly.

Also, we know according to Lenz's law a reverse current will be induced that will oppose the cause which has produced it. And so, due to the induced current, the polarity of the inductor will get reversed. This reverse polarity of the inductor forward biases the diode present in the circuit. This provides the path for the current through the diode that flows through the load during the off state of the chopper i.e., T_{off} . However, we

must note here that the current through the inductor is of decreasing nature and will die out after a point in time.

Thus, the total voltage across the load will be given as:

$$V_{\text{out}} = V_{\text{in}} + V_L \quad (\text{II. 25})$$

This means that the output voltage exceeds the applied input voltage. Thus, performs step-up conversion as the energy stored within the inductor during the T_{on} period is released during the T_{off} period.

During the T_{on} period, the voltage across the inductor will be given as:

$$V_L = L \frac{di}{dt} \quad (\text{II. 26})$$

Let us have a look at the waveform representation of the step-up chopper shown below:

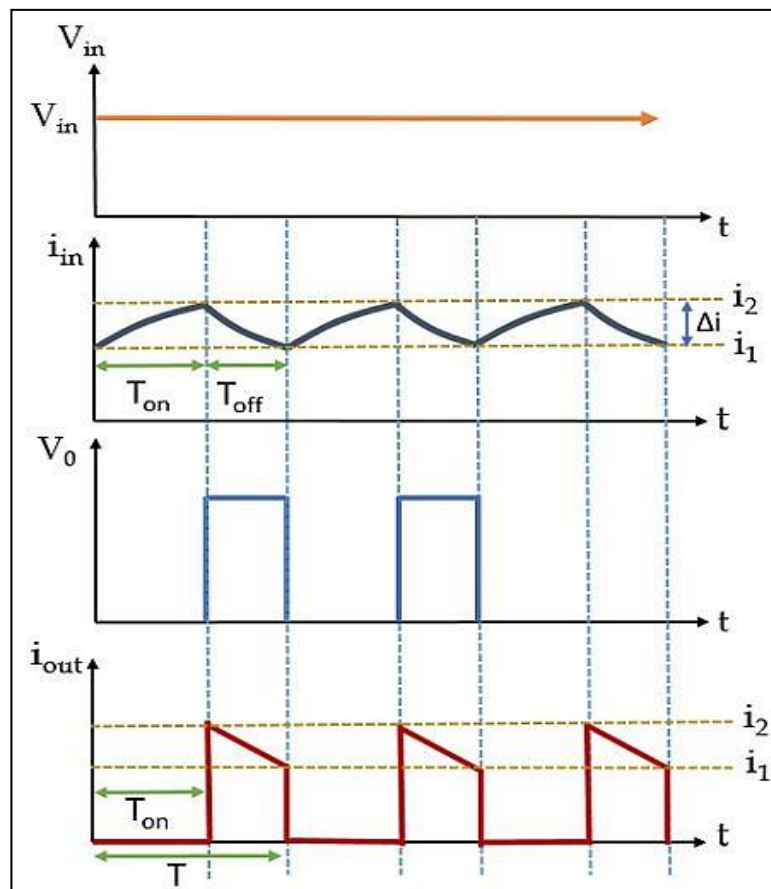


Figure II.10: Waveform Representation

During the T_{on} period, the current through the inductor will change from i_1 to i_2 this is clearly shown above. While during the T_{off} period, the inductor current will change from i_2 to i_1 . Now, talking about voltage, so during the turn-on period, the voltage across the inductor will be equal to the supply input voltage. But when CH gets off then on applying KVL in the figure shown above, we will get,

$$V_L - V_0 + V_{in} = 0 \quad (II. 27)$$

This means,

$$V_L = V_0 - V_{in} \quad (II. 28)$$

Considering that output current is varying linearly, the energy input provided by the source to the inductor, when CH is on, is given as:

$$W_{on} = (\text{voltage across the inductor})(\text{average current through the inductor})T_{on}$$

$$W_{on} = V_{in} \left(\frac{i_1 + i_2}{2} \right) T_{on} \quad (II. 29)$$

Further, the energy that the inductor releases to the load when CH is off is given as:

$$W_{off} = (\text{voltage across the inductor})(\text{average current through the inductor})T_{off}$$

$$W_{off} = V_{out} - V_{in} \left(\frac{i_1 + i_2}{2} \right) T_{off} \quad (II. 30)$$

For a lossless system, comparing the two energies, we will have,

$$V_{in} \left(\frac{i_1 + i_2}{2} \right) T_{on} = V_{out} - V_{in} \left(\frac{i_1 + i_2}{2} \right) T_{off} \quad (II. 31)$$

On simplifying,

$$V_{in} T_{on} = V_{out} T_{off} - V_{in} T_{off} \quad (II. 32)$$

$$V_{out} T_{off} = V_{in} T_{on} + V_{in} T_{off} \quad (II. 33)$$

$$V_{out} T_{off} = V_{in} (T_{on} + T_{off}) \quad (II. 34)$$

Since we know, $T = T_{on} + T_{off}$, therefore,

$$V_{out} T_{off} = V_{in} T \quad (II. 35)$$

$$V_{out} = V_{in} \frac{T}{T_{off}} \quad (II. 36)$$

$$V_{out} = V_{in} \frac{T}{T - T_{on}} \quad (II. 37)$$

$$V_{out} = V_{in} \frac{1}{\left(\frac{T}{T} - \frac{T_{on}}{T}\right)} \quad (II. 38)$$

Since, we know, duty cycle i.e., $\alpha = T_{on}/T$

$$V_{out} = V_{in} \frac{1}{(1 - \alpha)} \quad (II. 39)$$

Thus, we can conclude here that the average load voltage can be stepped up with the change in the duty cycle.

II.4.3. Buck-Boost Converter :

The buck–boost converter is a type of DC-to-DC converter that has an output voltage magnitude that is either greater than or less than the input voltage magnitude. It is used to “step up” the DC voltage, similar to a transformer for AC circuits. It is equivalent to a fly-back converter using a single inductor instead of a transformer. Two different types are called buck–boost converter DC-DC converters, commonly referred to as choppers, include the versatile Buck-Boost converter. This converter can function as either a step-down or step-up converter, depending on its duty cycle, denoted as DA typical Buck-Boost converter circuit is shown below:

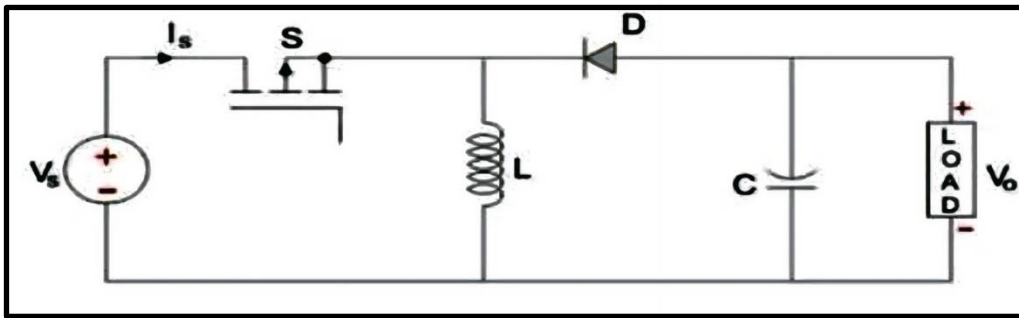


Figure II.11: The Circuit Representation of Buck-Boost Converter

The input voltage source is connected to a solid-state device. The second switch used is a diode. The diode is connected, in reverse to the direction of power flow from source, to a capacitor and the load and the two are connected in parallel as shown in the figure above.

The controlled switch in the converter uses Pulse Width Modulation (PWM) to toggle on and off. PWM may operate based on time or frequency, with time-based being the more common approach.

Frequency-based modulation, though versatile, has the disadvantage of requiring a wide range of frequencies to precisely control the switch and thus achieve the desired output voltage.

Time based Modulation is mostly used for DC-DC converters. It is simple to construct and use.

The frequency remains constant in this type of PWM modulation. The Buck Boost converter has two modes of operation. The first mode is when the switch is on and conducting.

II.4.3.1 Mode I: Switch is ON, Diode is OFF:

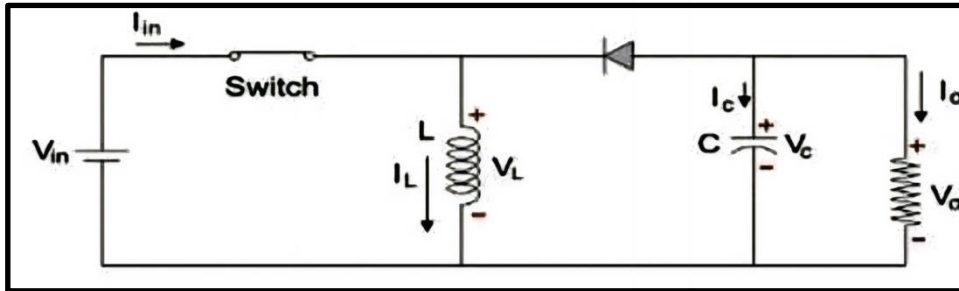


Figure II.12: The Equivalent Circuit of Mode I

The Switch is ON and therefore represents a short circuit ideally offering zero resistance to the flow of current so when the switch is ON all the current will flow through the switch and the inductor and back to the DC input source.

The inductor stores charge during the time the switch is ON and when the solid state switch is OFF the polarity of the Inductor reverses so that current flows through the load and through the diode and back to the inductor. So, the direction of current through the inductor remains the same.

Let us say the switch is on for a time T_{ON} and is off for a time T_{OFF} .

We define the time period, T , as:

$$T = T_{ON} + T_{OFF} \quad (\text{II. 40})$$

and the switching frequency:

$$f_{\text{switching}} = \frac{1}{T} \quad (\text{II. 41})$$

Let us now define another term, the duty cycle:

$$D = \frac{T_{ON}}{T} \quad (\text{II. 42})$$

Let us analyse the Buck Boost converter in steady state operation for this mode using KVL.

$$\begin{aligned} V_{in} &= V_L \\ V_L &= L \frac{di_L}{dt} = V_{in} \\ \frac{di_L}{dt} &= \frac{\Delta i_L}{\Delta t} = \frac{\Delta i_L}{DT} = \frac{V_{in}}{L} \end{aligned} \quad (\text{II. 43})$$

Since the switch is closed for a time $T_{ON} = DT$ we can say that $\Delta t = DT$.

$$(\Delta i_L)_{\text{closed}} = \left(\frac{V_{in}}{L} \right) DT \quad (\text{II. 44})$$

While performing the analysis of the Buck-Boost converter we have to keep in mind that

- The inductor current is continuous and this is made possible by selecting an appropriate value of L.
- The inductor current in steady state rises from a value with a positive slope to a maximum value during the ON state and then drops back down to the initial value with a negative slope. Therefore, the net change of the inductor current over any one complete cycle is zero.

II.4.3.2 Mode II: Switch is OFF, Diode is ON:

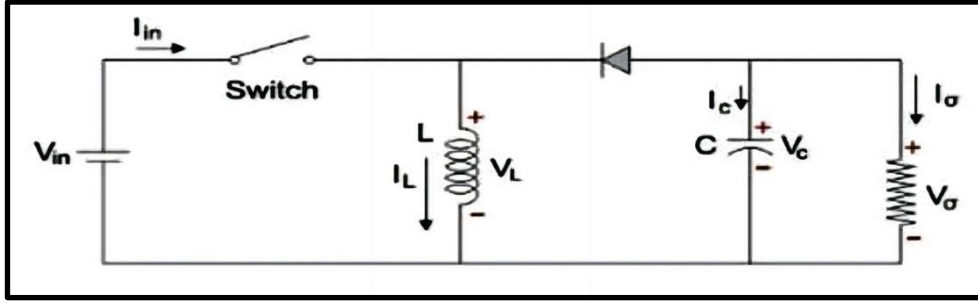


Figure II.13: The Equivalent Circuit of Mode II

In this mode the polarity of the inductor is reversed and the energy stored in the inductor is released and is ultimately dissipated in the load resistance and this helps to maintain the flow of current in the same direction through the load and also step-up the output voltage as the inductor is now also acting as a source in conjunction with the input source. But for analysis we keep the original conventions to analyse the circuit using KVL.

II.4.3.3 Buck Boost Converter Formula:

Let us now analyse the Buck Boost converter in steady state operation for Mode II using KVL.

$$V_L = V_o \quad (\text{II. 45})$$

$$V_L = L \frac{di_L}{dt} = V_o \quad (\text{II. 46})$$

$$\frac{di_L}{dt} = \frac{\Delta i_L}{\Delta t} = \frac{\Delta i_L}{(1-D)T} = \frac{V_o}{L} \quad (\text{II. 47})$$

Since the switch is open for a time

$$T_{OFF} = T - T_{ON} = T - DT = (1-D)T \quad (\text{II. 48})$$

we can say that

$$\Delta t = (1-D)T \quad (\text{II. 49})$$

$$(\Delta i_L)_{\text{open}} = \left(\frac{V_o}{L} \right) (1-D)T \quad (\text{II. 50})$$

It is already established that the net change of the inductor current over any one complete cycle is zero.

$$(\Delta i_L)_{\text{closed}} + (\Delta i_L)_{\text{open}} = 0 \quad (\text{II. 51})$$

$$\left(\frac{V_o}{L}\right)(1-D)T + \left(\frac{V_{\text{in}}}{L}\right)DT = 0 \quad (\text{II. 52})$$

$$\frac{V_o}{V_{\text{in}}} = \frac{-D}{1-D} \quad (\text{II. 53})$$

We know that D varies between 0 and 1. If $D > 0.5$, the output voltage is larger than the input; and if $D < 0.5$, the output is smaller than the input. But if $D = 0.5$ the output voltage is equal to the input voltage[8].

II.5.Comparison of Converter Types :

Table (II.1) summarizes the voltage gains and switch stresses for the different converter types. For these converters, the evolution of the voltage gains as a function of the duty cycle is shown. While several types can be considered as boost converters, particularly if the duty cycle is greater than 0.5, only the boost type provides a boosting capability over the entire duty cycle range. For a duty cycle of 0.5 for example, the boost converter exhibits an output voltage twice the input voltage. Whereas for the other boost-derived type, the output voltage is equal to the input voltage for this duty cycle value. It is only when the duty cycle approaches 1 that the other boost-derived types tend to resemble the behavior of the conventional boost type.[9].

Converter /Parameters	Voltage Gain $\frac{V_{\text{out}}}{V_{\text{in}}}$	Voltage Controls $V_{k,\text{max}} = V_{d,\text{max}} $	Current Controls $i_{k,\text{max}} = V_{d,\text{max}} = i_{d,\text{max}}$
Boost	$\frac{1}{1-\alpha}$	$\frac{V_{\text{in}}}{1-\alpha} + \frac{\Delta V_{\text{out}}}{2}$	$\frac{I_{\text{out}}}{1-\alpha} + \frac{\Delta I_L}{2}$
Buck	$\frac{\alpha}{1-\alpha}$	$\frac{V_{\text{in}}}{1-\alpha} + \frac{\Delta V_{\text{out}}}{2}$	$\frac{V_C}{1-\alpha} + \frac{\Delta V_{\text{out}}}{2}$
Buck-Boost	α	V_{in}	$i_L + \frac{\Delta I_L}{2}$

Table II.1: Comparison of Converter Types.**II.6. Efficiency of Static Converters :**

The table provides insight into the efficiency of some well-known converter types. [10]

Structure	Conversion Efficiency	Battery
Boost	92%	24V
Buck	93%	12V
Buck-Boost	92%	12-24V

Table II.2: Efficiency of Static Converters.**II.7. Conclusion :**

In conclusion, DC-DC converters are fundamental to modern power electronics, ensuring efficient voltage regulation and management across diverse applications. Through versatile topologies such as buck, boost, and buck-boost, these devices facilitate critical operations in the automotive, telecommunications, and renewable energy sectors. Notably, their integration with Maximum Power Point Tracking (MPPT) technology is essential for optimizing energy extraction in photovoltaic systems. The following chapter will provide a detailed technical analysis of MPPT mechanisms and their implementation strategies.

**Chapter III:
Maximum
Power Point
Tracking**

III.1.Introduction :

To mitigate the inherent performance limitations of photovoltaic (PV) panels and maximize overall system efficiency, comprehensive optimization of the PV architecture is required, a critical component in this optimization process is the DC-DC converter, which functions as the power interface between the PV generator and the load. By integrating a Maximum Power Point Tracking (MPPT) controller, the converter can dynamically adjust the operating point to ensure continuous maximum power extraction, thereby minimizing energy transfer losses under fluctuating atmospheric conditions, such as varying solar irradiance and ambient temperature.

Since the 1970s, an extensive array of MPPT control methodologies has been developed, ranging from rudimentary feedback mechanisms based on voltage and current states to sophisticated algorithmic controllers designed for precise MPP detection, Among the most prevalent techniques documented in the literature are the Perturb and Observe (P&O) method, the Incremental Conductance (INC) approach, and the Hill Climbing algorithm [11].

III.2.Maximum Power Point Tracking :

The optimization of photovoltaic (PV) system efficiency is fundamentally dependent on maximizing the power output of the PV generator.

This is achieved through the strategic selection of the operating point, effectively matching the load impedance to the voltage source characteristics, in this architecture, the DC-DC converter functions as a dynamic impedance adapter, ensuring that the system operates at the optimal point to facilitate maximum energy production [12].

Consequently, the process of maximizing power output involves a continuous search for this optimal operating point, a control strategy formally known as Maximum Power Point Tracking (MPPT), these methodologies utilize iterative search algorithms to determine the specific solar module operating coordinates that yield peak power without interrupting system functionality.

The algorithms rely on the real-time calculation of extracted power by measuring and multiplying the module's instantaneous voltage and current.

Various MPPT techniques are documented in the literature to pursue the actual Maximum Power Point (MPP), including the Constant Voltage method, the Constant Current method, the Incremental Conductance (INC) algorithm, and the Perturb and Observe (P&O) method, in the context of this work, the Perturb and Observe method has been selected for implementation due to its high degree of simplicity and ease of integration into the control system.

III.3. Working principle of MPPT :

Advanced control laws are designed to guide devices toward operating at the peak points of their characteristic curves without prior knowledge of these coordinates or the factors causing their displacement, in the context of energy generation, this optimization results in the identification of Maximum Power Points (MPP), a methodology frequently identified in scientific literature as Maximum Power Point Tracking (MPPT), the primary objective of such control systems is to execute a continuous search for the MPP while facilitating a precise impedance matching between the generator and its load to ensure the transmission of maximum available power [13].

To streamline the operational framework of this control strategy, a DC load is typically implemented, as demonstrated in this power stage, the MPPT controller must be coupled with a four-pole network that possesses adjustable degrees of freedom to enable dynamic adaptation between the PV source and the load, in photovoltaic applications, this four-pole interface is realized through a DC-DC converter, which ensures that the power extracted from the PV generator aligns with the theoretical maximum power ($P_{\max}$) before being transferred directly to the designated load.

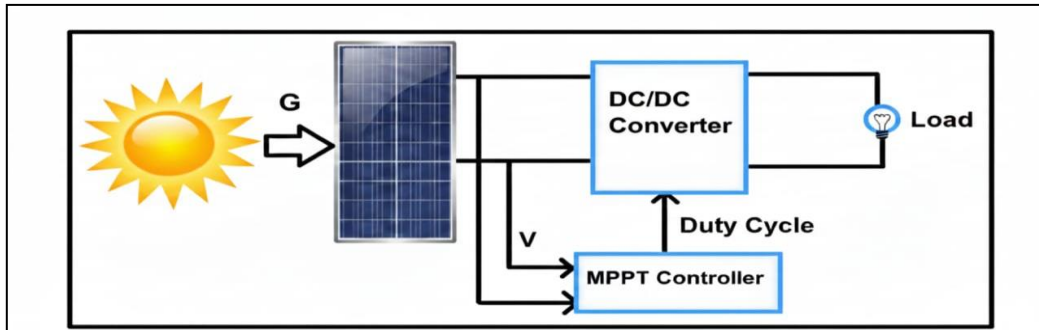


Figure III.1: Block Diagram of The PV System

The most prevalent control strategy involves the automatic adjustment of the duty cycle to maintain the generator at its optimal operating point, particularly in response

to sudden load or environmental fluctuations that may occur unpredictably, as illustrated in Figure (III.2), three distinct types of disturbances can shift the operating point from its initial maximum power point (MPP1) to a suboptimal position (P1).

In the event of a variation in solar irradiance (case a), the duty cycle must be precisely recalibrated to converge the system toward the new maximum power point (MPP2), similarly, in the case of a load variation (case b), the operating point undergoes a transition that necessitates a control command to re-establish an optimal position, to a lesser extent, shifts in the operating point may be attributed to fluctuations in the photovoltaic module's operating temperature (case c), although this requires an adjustment at the command level, it does not impose the same stringent time constraints as the two previously mentioned scenarios [14].

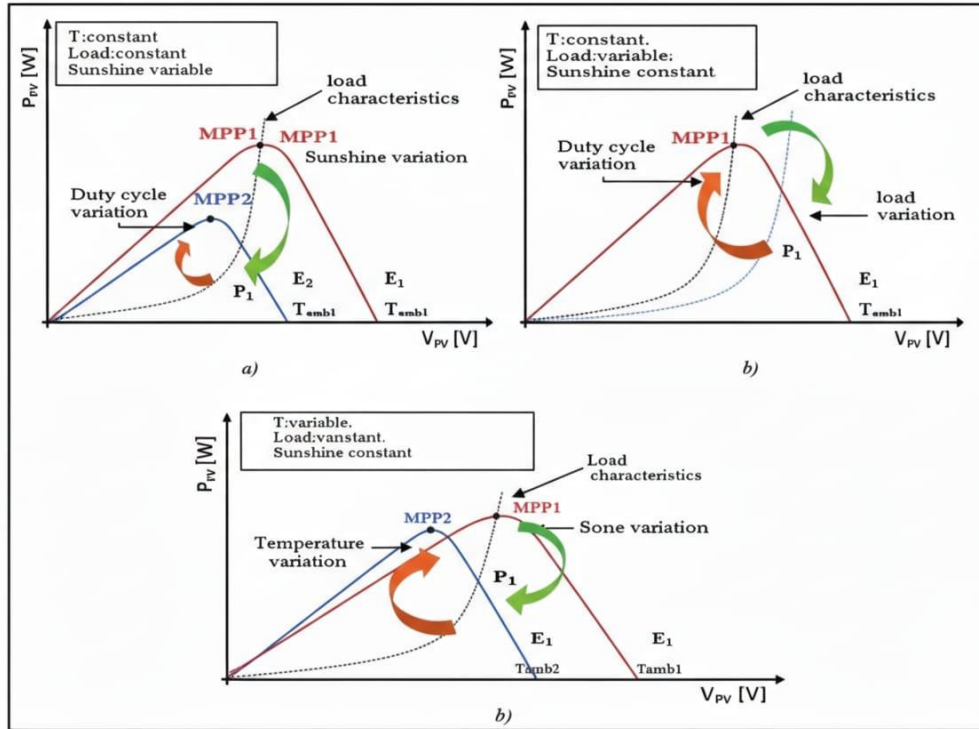


Figure III.2: Search and Recovery Of MPP

III.4. Classification of MPPT Control :

MPPT controllers are generally categorized according to their electronic implementation into analog, digital, or mixed architectures, however, a more robust classification methodology distinguishes these controllers based on the specific search

algorithms they execute and the nature of the input parameters processed by the MPPT system.

III.4.1. Classification of MPPT Controllers Based on Input Parameters:

III.4.1.1 MPPT Controllers Operating from Input Parameters :

A multitude of MPPT controllers execute a search for the maximum power point based on the dynamic evolution of the power delivered by the PV array, prominent examples include the Perturb and Observe (P&O) method and Incremental Conductance (INC) algorithms, both of which utilize instantaneous power values to implement precise control actions for effective MPP tracking, alternatively, some controllers rely on proportional relationships established between optimal parameters such as V_{opt} and I_{opt} and the intrinsic characteristic parameters of the PV module, specifically the open-circuit voltage V_{oc} and short-circuit current I_{sc} .

Notably, MPPT controllers inspired by Artificial Neural Networks are also classified within this category, these systems either employ extensive memory architectures to store comprehensive operational datasets or utilize advanced approximation techniques to determine the optimal point, overall, this class of controllers is characterized by significant advantages in terms of tracking precision and rapid response time [15].

III.4.1.2 MPPT Controllers Operating from Output Parameters of the Converter:

In the literature, there are also algorithms based on the output parameters of the DC-DC converters, for example, MPPT controllers centered on the maximization of the output current are primarily utilized when the load is represented by a battery, in all systems utilizing output parameters, an approximation of P_{max} is derived through the conversion efficiency of the power stage, in summary, the higher the efficiency of the conversion stage, the more valid this approximation becomes.

However, in general, all single-sensor systems are inherently characterized by a degree of imprecision, it is also notable that most of these control systems were originally engineered for specialized space applications [15].

III.4.2. Classification of MPPT Controllers According to the Type of Search :

III.4.2.1. Indirect MPPT:

This type of MPPT control utilizes the existing link between the measured variables or V_{oc} , which can be easily determined, and the approximate position of the MPP, it also includes controls based on an estimation of the operating point of the PV system made from a predefined parametric model, there are also controls that establish optimal voltage tracking by only considering variations in cell temperature provided by a sensor, these controls have the advantage of being simple to implement, they are mainly intended for inexpensive and imprecise systems operating in geographical areas with little climate change [16].

III.4.2.2 Direct MPPT:

This type of MPPT control determines the optimal operating point based on the currents, voltages, or powers measured in the system, it can therefore react to unpredictable changes in the operation of the PV system, generally, these procedures are based on a search algorithm, with which the maximum power point of the curve is determined without interrupting operation, to do this, the operating point voltage is incremented at regular intervals, if the output power is greater, then the search direction is maintained for the next step; otherwise, it is reversed, the actual operating point then oscillates around the MPP, this basic principle can be preserved by other algorithms against interpretation errors, these errors may occur, for example, due to a wrong search direction resulting from an increase in power due to a rapid increase in radiation levels, determining the value of the PV generator power, essential for finding the MPP, requires measuring the generator's voltage and current, and multiplying these two variables, other algorithms are based on introducing small-signal sinusoidal variations in the converter switching frequency to compare the alternating and direct components of the PV system voltage and thus place the PV system operating point as close as possible to the MPP, the advantage of this type of control is its precision and rapid reaction [16].

III.5. Different MPPT Commands Synthesis :

Various works on MPPT commands appear regularly in the literature since 1968, the date of publication of the first command law adapted to renewable energy specifically photovoltaic systems, given the large number of publications in this field,

we have a classification of different MPPT techniques according to their fundamental operating principles.

III.5.1. First MPPT Commands Types:

The algorithm implemented in the first MPPT command was relatively simple, indeed, the computational capacity of microcontrollers available at that time was limited and applications, particularly in the aerospace sector, faced fewer constraints regarding temperature fluctuations and solar irradiation levels, the pioneering command applied to a photovoltaic system was originally described by A.F. Boehringer, this control strategy was based on an adaptive control algorithm designed to maintain the system at its maximum power point (MPP), as illustrated in Figure 3, this logic can be efficiently implemented on a computer system where the controller calculates the instantaneous power at time t_i from measurements of I_{PV} and V_{PV} , subsequently comparing it to the previous value stored in memory from time t_{i-1} , based on this comparison, a revised duty cycle D is computed and applied to the static power converter..

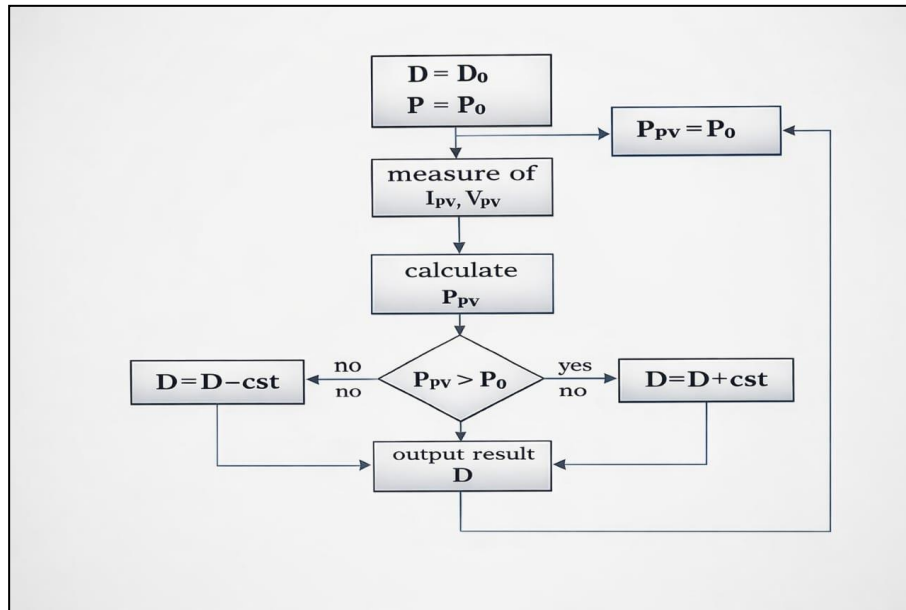


Figure III.3: Bloc Diagram of a Digital MPPT Command

This principle is always valid from a theoretical point of view and applied nowadays to more efficient numerical algorithms, however, the response time has been significantly improved alongside a substantial increase in the PPM search accuracy [14].

III.5.2. Efficient MPPT Commands Algorithms :

The three (04) methods most commonly encountered are commonly referred to respectively as Hill Climbing, Perturb & Observe (P&O), Incremental Conductance (INC), and Artificial Neural Networks (ANN).

III.5.2.1. Algorithm Perturb and Observe (P&O) :

The principle of MPPT commands of P & O types is to disrupt the voltage with a low amplitude around its initial value and analyze the behavior of the resulting power variation, thus, as shown in Figure (III.4), it can be deduced that if a positive increment of voltage generates an increase of power, the operating point is situated to the left of the maximum power point if however, the power decreases, this implies that the system has exceeded the maximum power point.

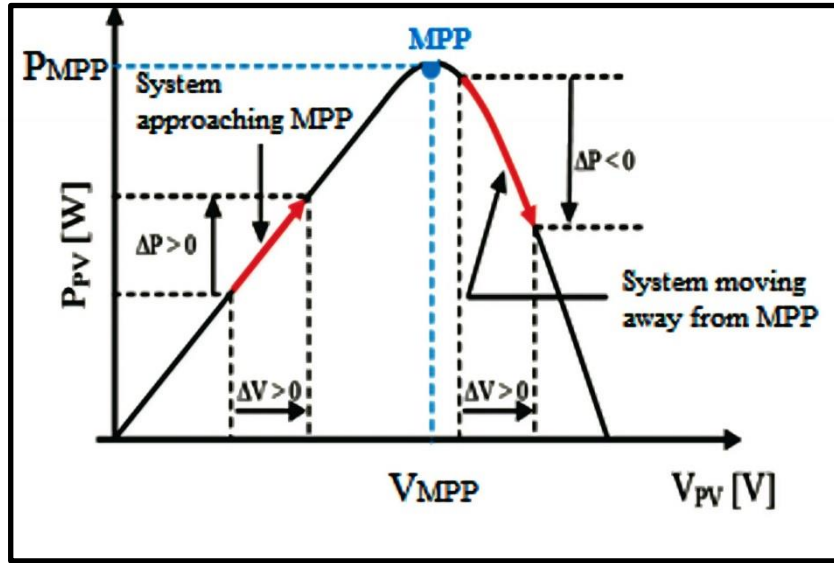


Figure III.4: Ppv VS Vpv Characteristic of a Solar Panel

Figure (III.5) shows the algorithm associated with a conventional MPPT command of the P & O type, where the evolution of the power is analysed after each voltage disturbance, for this type of command, two sensors (current and voltage) are required to determine the power of the solar generator at every instant of time, the Perturb & Observe method is nowadays widely utilized due to its ease of implementation, however, it presents certain challenges associated with steady-state oscillations around

the MPP, as the search for the maximum power point must be repeated periodically, causing the system to oscillate continuously around the optimal point.

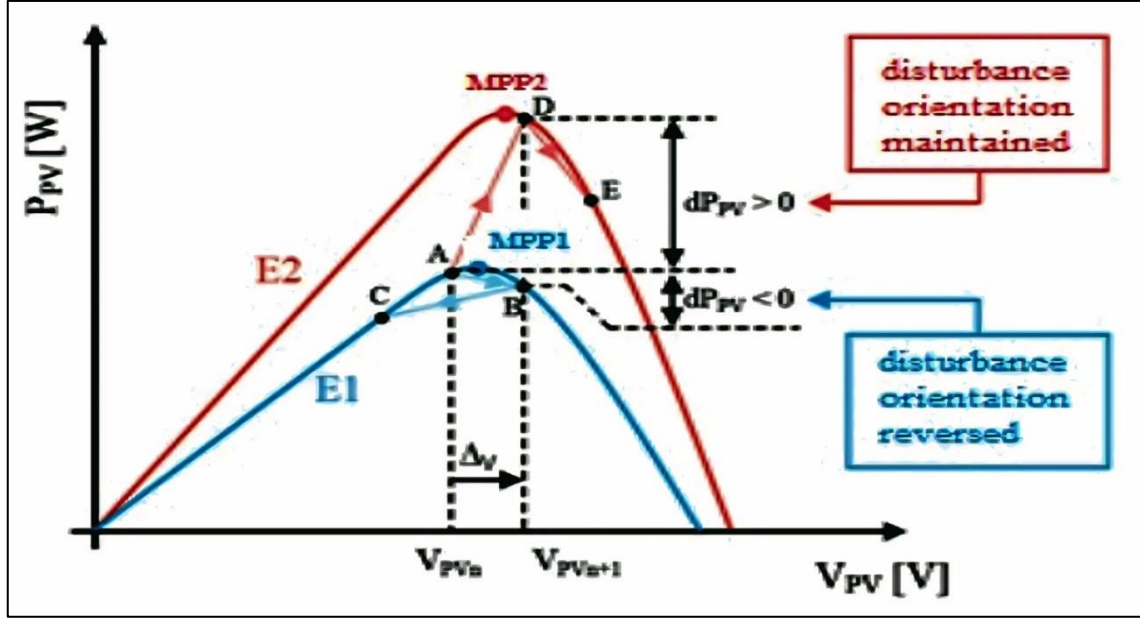


Figure III.5: Divergence of The P & O Command Due to Radiation Variations

Figure (III.6) shows a detailed algorithm of the P & O command.

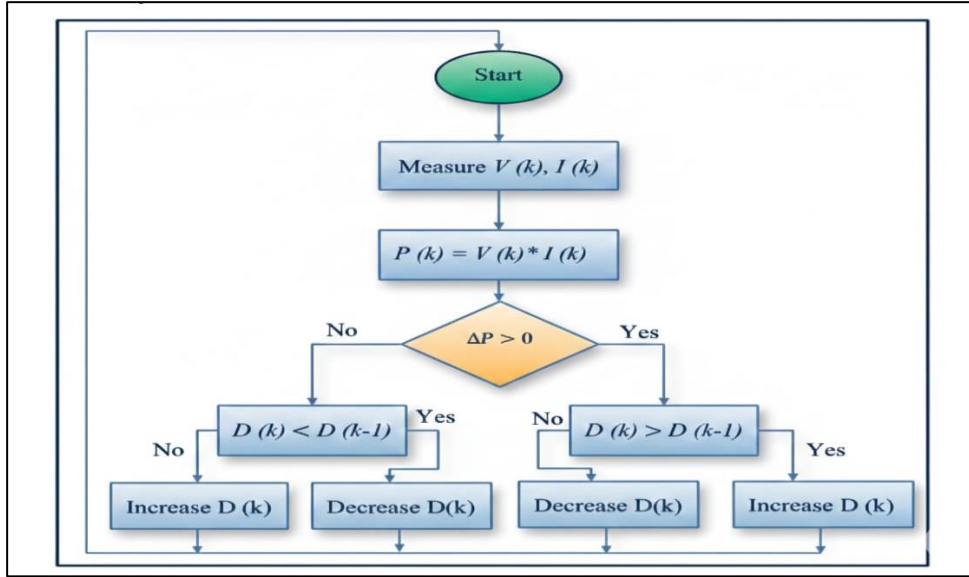


Figure III.6: Algorithm of The P & O Type of Command

To understand this, consider the example of a given solar irradiation, E1, with an operating point lying in A. following a voltage disturbance of value ΔV , it switches to B, implying a variation of operating without illumination, a reversal of the sign of the disturbance due to the detection of a negative sign for the derivative of the power resulting, in equilibrium, in oscillations around the MPP due to the path of the operating point between points B and C. it can be noted that losses of power transfer will be more

or less important depending on the respective positions of points B and C with respect to A. When changing the irradiation of the module from E1 to E2, the operating point then moves from A to D, which is interpreted in this case as a positive power variation[14].

III.5.2.2. Algorithm Hill Climbing :

The best thing about the hill climbing MPPT method is its simplicity, it uses the duty cycle D of the boost converter as a feedback parameter when the task of the MPPT is carried out [17], [18], the main disadvantage of this technique is due to the trade-off between the stability of the system in a period of constant irradiation, another disadvantage is the absence of a rapid response in case of a rapid change in radiation [17], [18].

The period of steady radiation requires a very small value of variation in the duty cycle ΔD to avoid a strong oscillation of the power about the peak power point, reducing the energy captured by the PV, on the other hand, rapidly changing irradiation requires a higher duty cycle value to accelerate the pursuit of peak power..

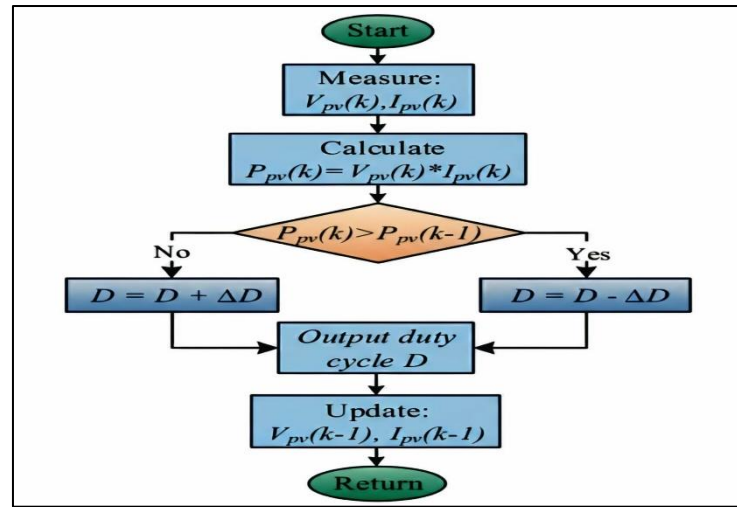


Figure III.7: State Flowchart of Hill Climbing MPPT Technique.

III.5.2.3. Algorithm Incremental conductance (INC) :

The principle of this algorithm is based on knowing the conductance $G = I/V$ and its increment dG to determine the operating point relative to the maximum power point, if dG exceeds $-G$, the duty cycle is decreased, whereas if dG is less than $-G$, the duty cycle is increased, this iterative process continues until the maximum power point is precisely reached [19].

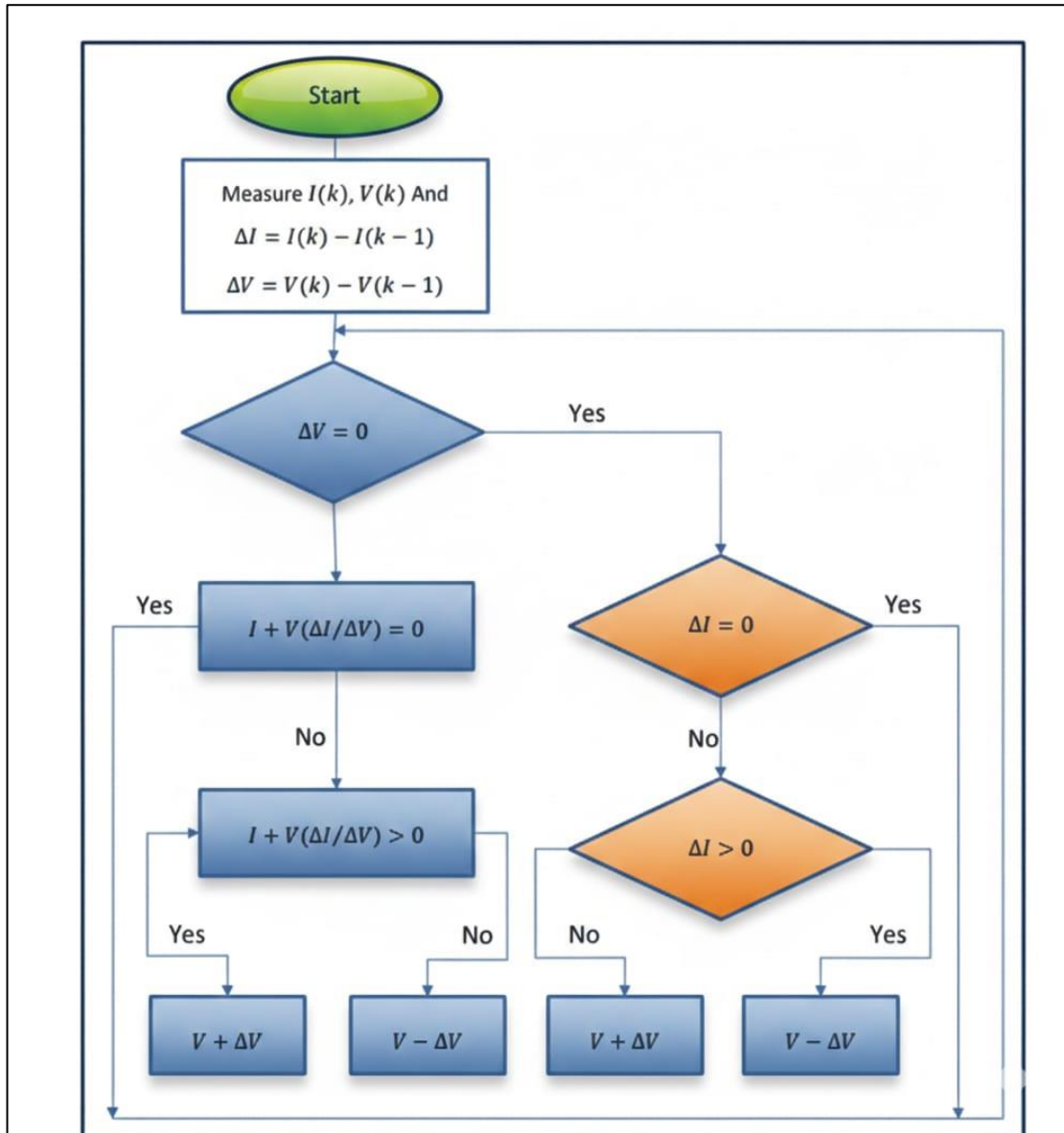


Figure III.8: Flowchart for The Incremental Conductance Algorithm.

III.5.2.4. Algorithm Fuzzy Logic Control (FLC):

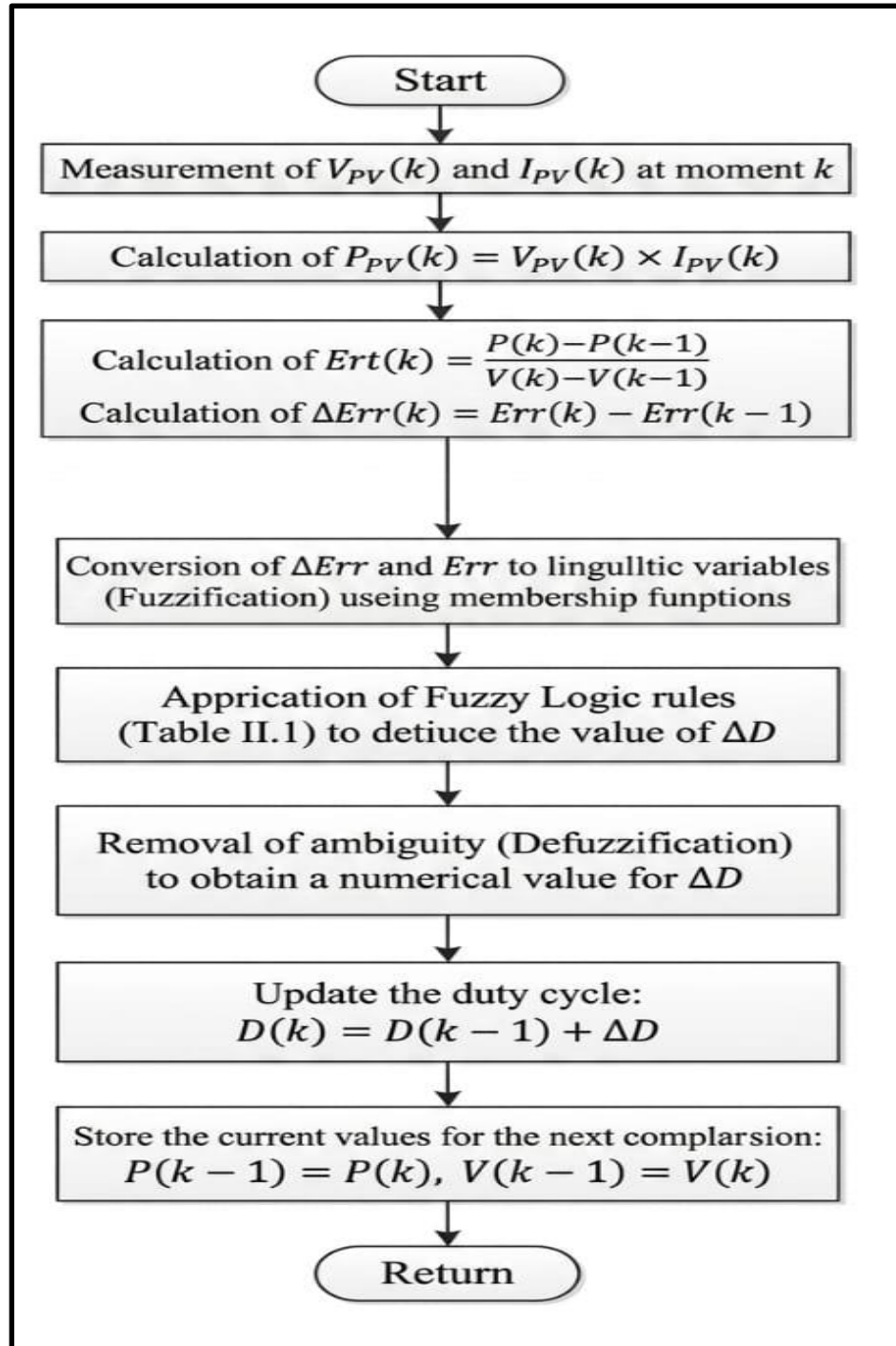


Figure III.9: Flowchart for The Fuzzy Logic Control Algorithm

Fuzzy Logic is a sophisticated form of many-valued logic that operates on approximate reasoning rather than the rigid, binary "true or false" distinctions of traditional logic. By allowing variables to exist in varying degrees of truth, FLC provides a framework that effectively mirrors human-like decision-making. In practical applications, this enables the controller to achieve high processing speeds while maintaining an acceptable level of precision [50].

The primary objective of the FLC is to dynamically track and extract the maximum power from the PV system under specific irradiance (W/m^2) and temperature ($^{\circ}\text{C}$) levels. A key advantage of FLC is its "model-free" nature; it does not require prior technical knowledge of the PV system's internal parameters. This simplicity allows the controller to remain highly efficient in tracking the Maximum Power Point (MPP) even under rapidly changing atmospheric conditions [51].

The control logic is driven by two inputs Error (Err) and Change in Error (ΔErr) which are derived from the PV output power and voltage as follows:

(II. 1)

$$\text{Err} = \frac{P_{pv}(K) - P_{pv}(K - 1)}{V_{pv}(K) - V_{pv}(K - 1)}$$

$$\Delta \text{Err} = \text{Err}(K) - \text{Err}(K - 1) \quad (\text{II. 2})$$

The final output of the FLC, determined through the defuzzification process, is the required adjustment in the duty cycle (ΔD) of the DC–DC converter. The architectural layout of this process is illustrated in Figure (II.15).

The widespread adoption of FLC is attributed to its versatility as a universal, adaptive, and simple control algorithm. It is characterized by its fast tracking response and its ability to function effectively even with imprecise input data or parameter variations. Furthermore, FLC demonstrates superior efficiency in MPP tracking during volatile weather patterns [52]. However, a significant drawback occurs during Partial Shading Conditions (PSC), where the algorithm may become trapped at a Local Peak (LP) rather than the global maximum.

The membership functions for both inputs and outputs are depicted in Figure (II.16), while the linguistic fuzzy rules are detailed in Table (II.1) [53]. Once the numerical inputs are transformed into fuzzy variables, the FLC estimates the appropriate change in the duty ratio to ensure the boost converter operates at peak efficiency.

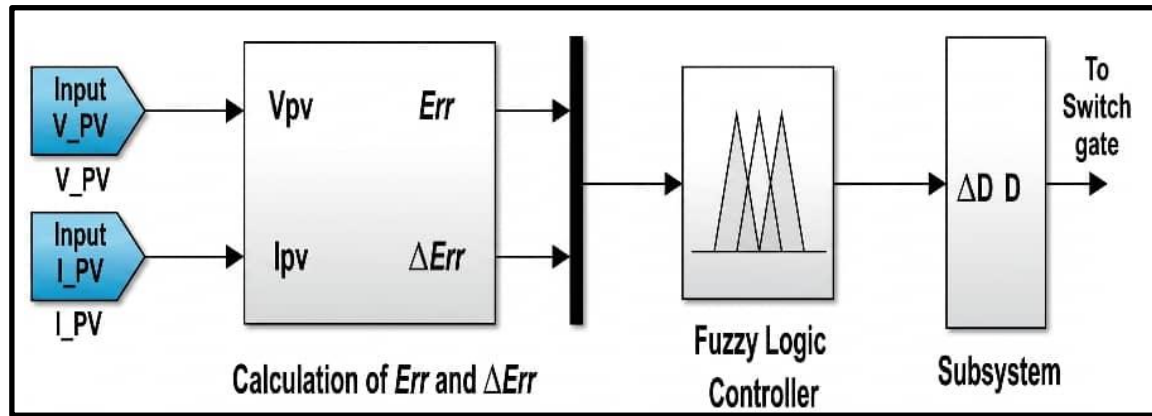


Figure III.10: FLC block diagram in MATLAB/Simulink

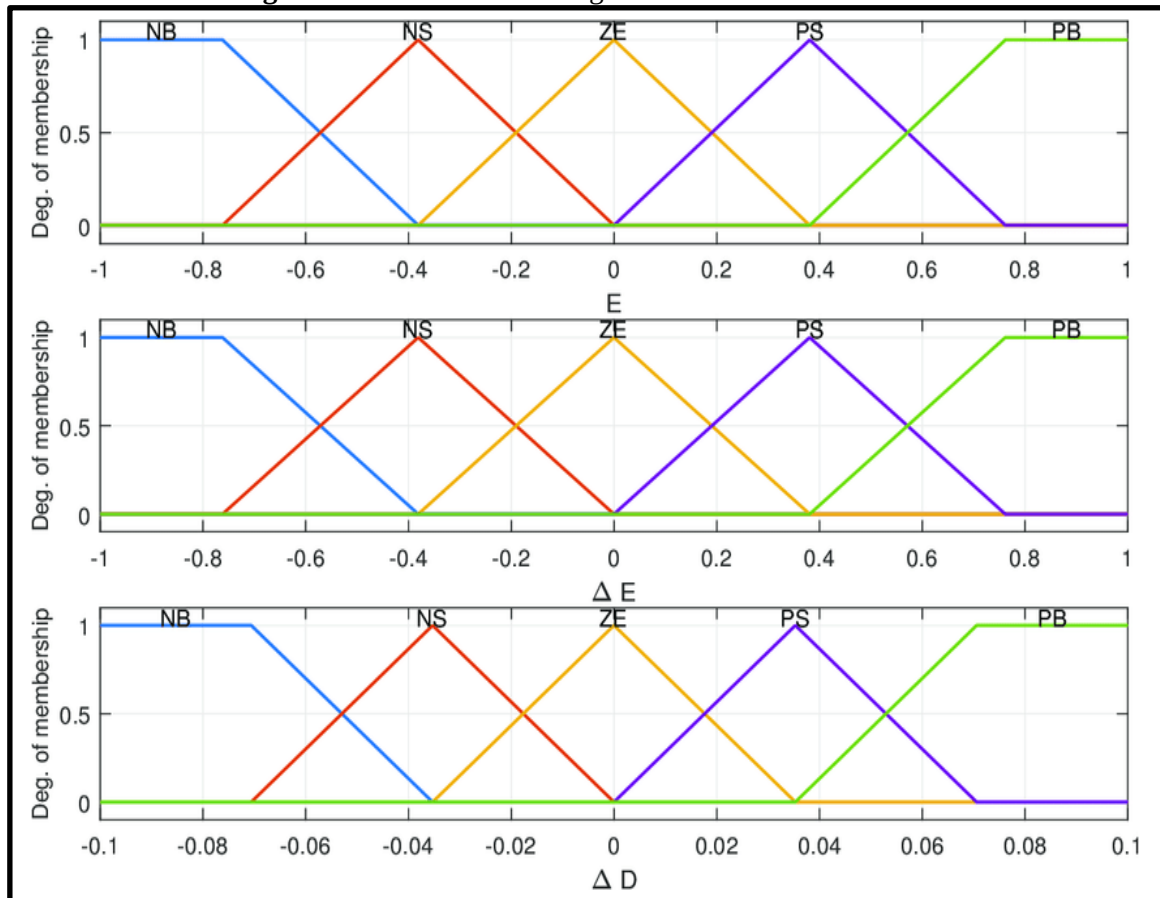


Figure III.11: Membership functions of FLC

E_{rr}	ΔE_{rr}						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

Table III.1: Fuzzy rules for the input and output variables

NB: Negative Big **NM:** Negative Medium **NS:** Negative Small
PB: Positive Big **PM:** Positive Medium **PS:** Positive Small
ZE: Zero

The implementation of this technique for a solar PV system is represented in figure (II.17). In fuzzification, the inputs of PV parameters are transformed into the linguistic variables, crisp quantity is converted into fuzzy quantity (fuzzy set).

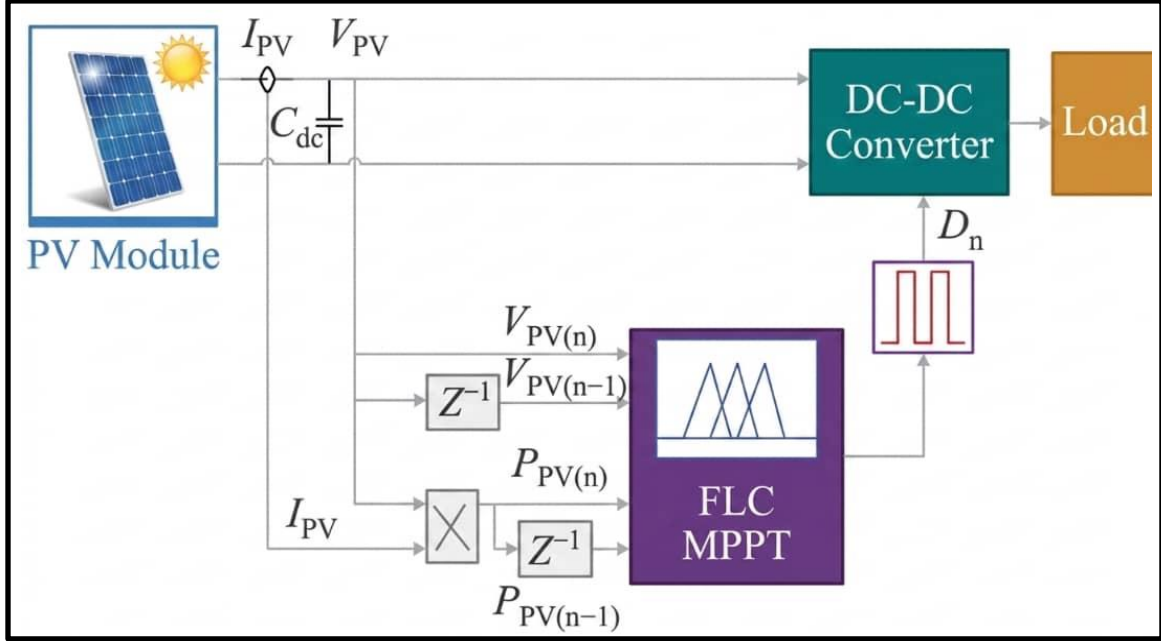


Figure III.12: Block diagram of FLC MPPT technique

Research indicates that Adaptive FLC demonstrates superior performance compared to both direct and indirect FLC-based MPPT methods, maintaining high efficiency during both dynamic and steady-state conditions, irrespective of the converter topology employed [54].

However, to overcome its inherent limitations, it is often concluded that FLC should be integrated with scanning-and-storing algorithms or other artificial intelligence techniques. Such hybrid approaches are essential for successfully navigating Partial Shading Conditions (PSC), ensuring that the system tracks the Global Peak (GP) with high precision, rapid convergence, and effective drift avoidance [55].

The following summary outlines the practical strengths and challenges of employing FLC-based MPPT in PV systems:

Core Advantages:

Operational Robustness: Offers a fast response time and superior performance with the flexibility to adjust accuracy based on system needs.

Steady Performance: Significantly reduces oscillations during atmospheric transitions, ensuring a more stable power output.

Tolerance to Imprecision: Capable of maintaining high efficiency even when dealing

with noisy or imprecise input data.

Synergistic Potential: Becomes markedly more effective when coupled with Evolutionary Algorithms (EA) or other optimization techniques.

Model Independence: Eliminates the need for complex mathematical modeling or exhaustive technical data of the PV system.

Technical Disadvantages

Design Complexity: The offline development phase can be complex and resource-intensive, as it requires substantial prior information to establish the logic.

Subjectivity: The overall system efficiency is heavily reliant on the designer's expertise and the precision with which the fuzzy rules are defined.

Dynamic Convergence Issues: In certain highly volatile states, the controller may struggle to achieve stable convergence.

Static Rule Base: A significant practical constraint is that once the fuzzy rules are defined and implemented, they cannot be easily modified or updated.

III.5.2.5. Artificial Neural Networks (ANN) :

Generally, an artificial neural network utilizes numerous processors working simultaneously and arranged in different layers, the initial layer receives raw data inputs, analogous to the function of optic nerves in human biological systems, afterward, each subsequent layer processes the outputs transmitted from the preceding stage, mimicking the hierarchical signal transmission between biological neurons, the final layer then generates the system's ultimate results or operational outputs..

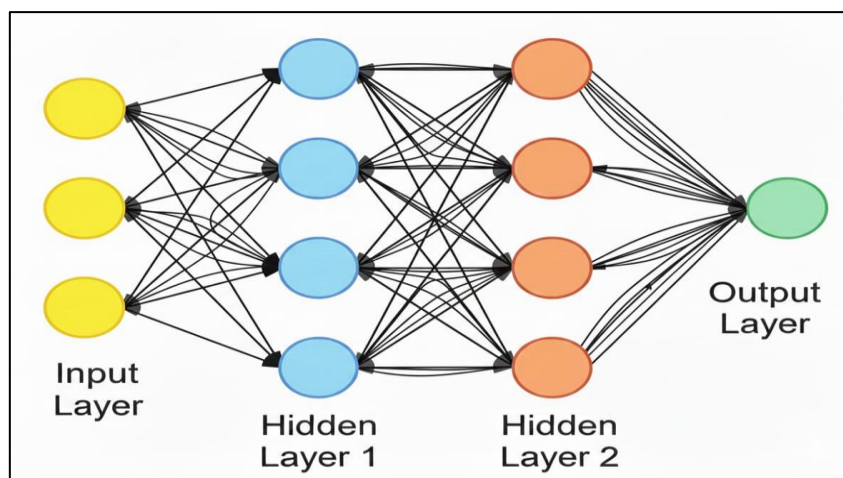


Figure III.13: Functioning of Artificial Neural Networks

Neural networks enable computers to learn from new data through specialized algorithms, systems integrated with these networks are trained on labeled datasets to master tasks like object recognition by identifying complex patterns within the examples, unlike traditional deterministic algorithms, neural networks are not directly programmed but evolve through a process analogous to the development of a human brain, consequently, there are three primary learning methodologies employed to achieve this cognitive capability:

1. **Supervised Learning** : The algorithm trains on labeled data and adjusts until it can achieve the desired output, this iterative refinement ensures the system's accuracy in predicting outcomes based on the provided inputs.
2. **Unsupervised Learning** : The network analyzes unlabeled data, with a cost function guiding it towards the desired result by indicating deviations, this allows the system to discover hidden patterns and structures within the information without prior labels.
3. **Reinforcement Learning** : The network is rewarded for positive results and penalized for negative ones, enabling it to learn and improve over time like humans learn from mistakes, this feedback mechanism allows the system to optimize its decision-making through trial and error.

III.5.2.6. Application of Artificial Neural Networks in MPPT :

Integrating artificial neural networks into photovoltaic systems facilitates the optimization of maximum power point tracking (MPPT), these advanced models significantly enhance the efficiency of solar energy harvesting by dynamically modulating the operating point of PV panels to ensure peak power output, such adjustments are essential to mitigate the effects of fluctuating environmental variables such as solar irradiance, temperature, and partial shading, consequently, ANN-based controllers empower PV systems to maximize their energy yield under diverse operating conditions.

The practical implementation of these computational models demonstrates their critical importance in advancing the performance of PV systems through sophisticated MPPT algorithms [20].

III.5.2.7. Implementation of ANN in MATLAB/SIMULINK :

Utilizing the Neural Network Fitting app in MATLAB offers a streamlined environment for the design, training, and validation of artificial neural networks, this process encompasses data selection, architectural configuration, and the rigorous assessment of performance through specialized metrics and graphical plots, such a tool proves indispensable for MPPT applications where the precise modeling of nonlinear relationships between system inputs and outputs is mandatory.

1. Data Collection :

Constructing a robust ANN-based MPPT model begins with the systematic acquisition of data from comprehensive simulations covering diverse operational scenarios, this gathered data serves as the fundamental cornerstone for both the training phase and the subsequent performance evaluation of the neural controller [20].

2. Setting Up the Neural Network Fitting Tool :

Initiating the implementation requires launching the MATLAB Neural Network Fitting Tool to access its intuitive interface designed for high-level neural network management, within this environment, the predefined variables are imported and the tool parameters are finely tuned to meet the specific requirements of the photovoltaic application [21].

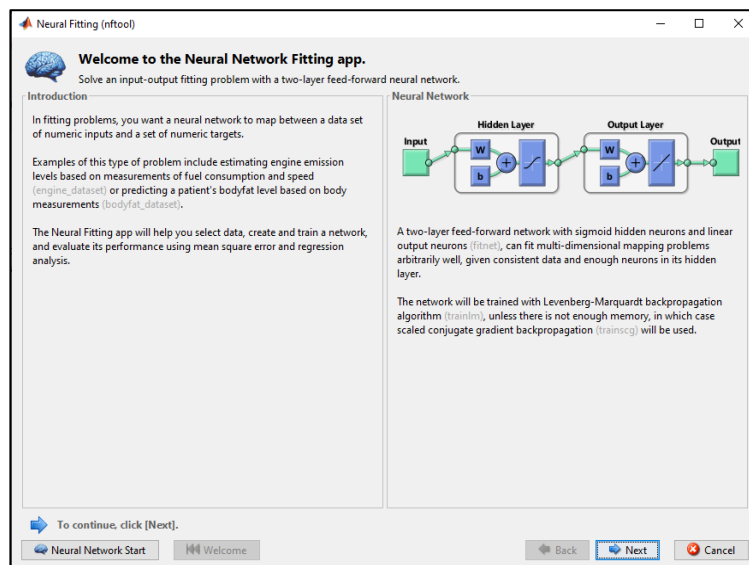


Figure III.14: Setting Up the Neural Network Fitting Tool

This figure introduces the Neural Network Fitting app, explaining its purpose, which is to solve an input-output fitting problem using a two-layer feed-forward neural network.

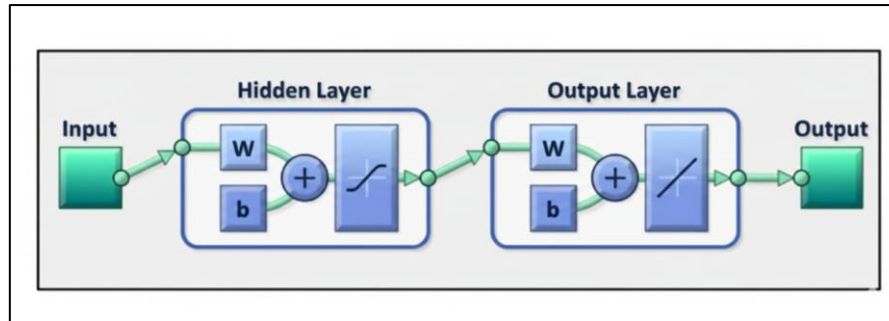


Figure III.15: Neural Network Structure

The diagram shows the structure of the neural network, which includes an input layer, hidden layers, and an output layer.

Training Algorithm: It mentions that the network will be trained using the Levenberg-Marquardt backpropagation algorithm (trainlm).

3. Select Data :

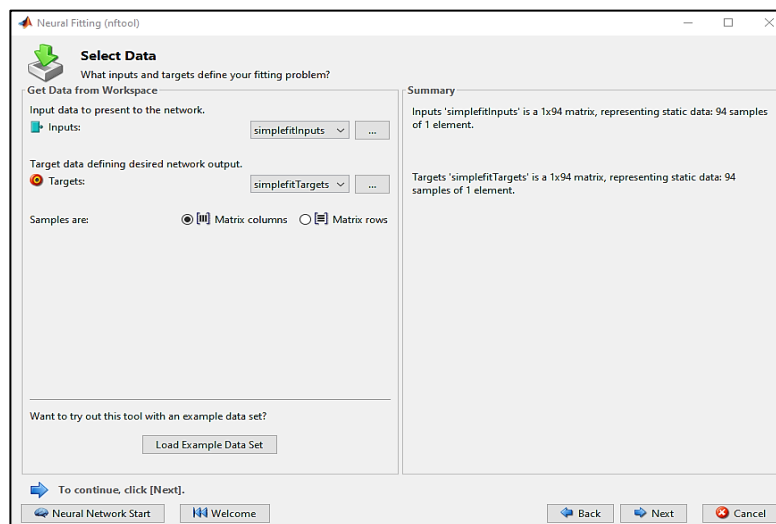


Figure III.16: Select Data

Inputs and Targets : This figure allows you to select the input and target data from the MATLAB workspace.

Data Summary : The summary on the right shows the dimensions of the selected data. Here, 'simplefitInputs' and 'simplefitTargets' are used as example datasets, with 94 samples each.

4. Import Data :

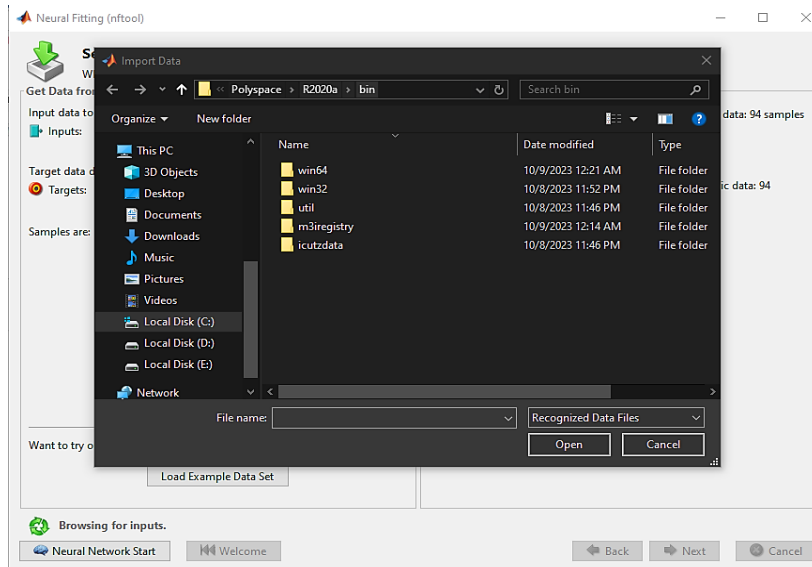


Figure III.17: Import Data

Data Import: If the data is not already in the workspace, this figure allows you to browse and import data files from your computer. This ensures that the input and target datasets are correctly loaded into MATLAB for network training.

5. Validation and Test Data :

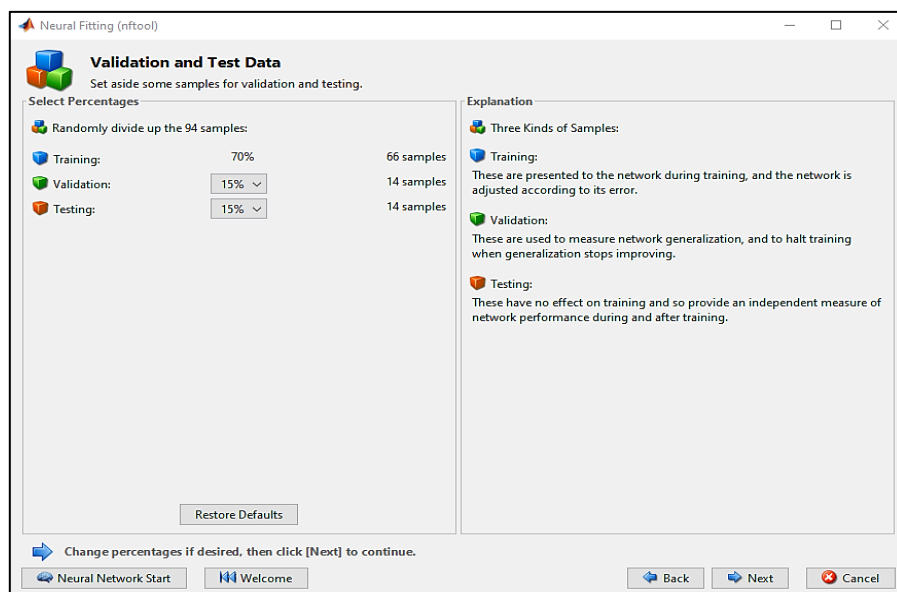


Figure III.18 : Validation and Test Data

Data Division: This figure divides the dataset into training, validation, and testing subsets. The default division is 70% training, 15% validation, and 15% testing.

Explanation: Training data is used to train the network, validation data is used to prevent overfitting by stopping training when performance worsens, and testing data is used to independently assess the network's performance.

1. Network Architecture :

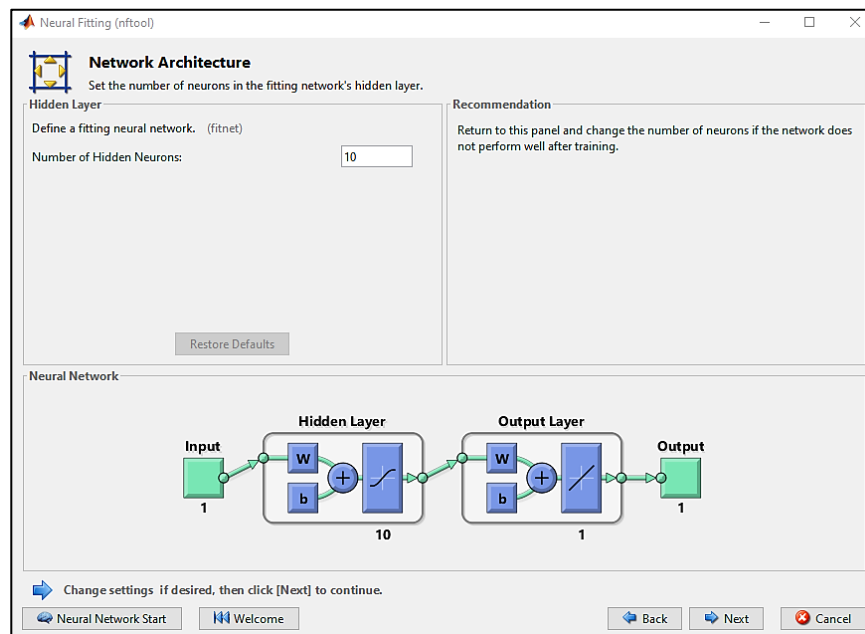


Figure III.19: Network Architecture

Hidden Layer Configuration: This figure allows you to set the number of neurons in the hidden layer(s). In this example, there are 10 neurons in the hidden layer[21].

Network Diagram: The diagram below visually represents the structure of the network with the specified number of hidden neurons.

2. Network Training :

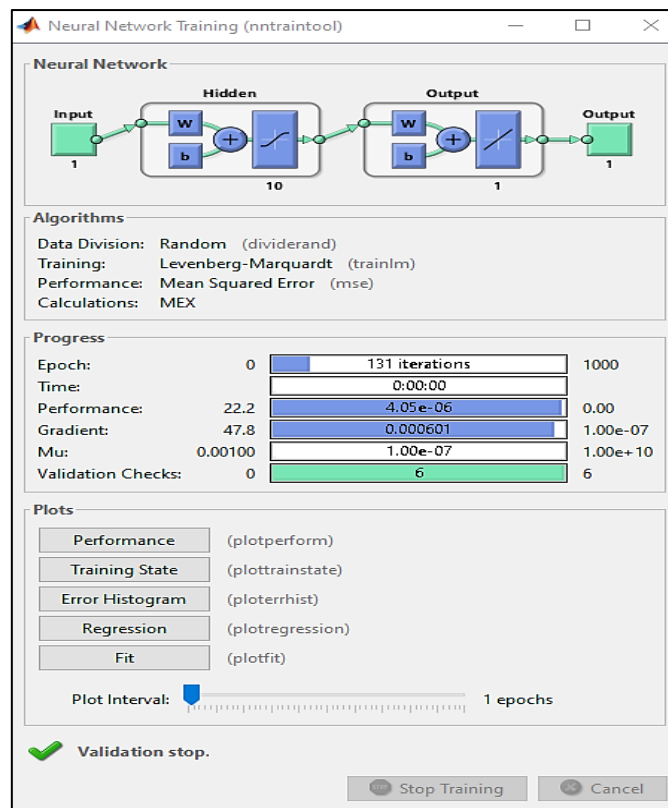


Figure III.20: Network Training

Training Process: This figure shows the progress of the network training, including the number of epochs, performance, gradient, and validation checks.

Performance Plots: Various plots are available to monitor the training process, including performance, training state, error histogram, and regression plots.

Stop Training: You can manually stop the training process if needed[22].

3. Train Network :

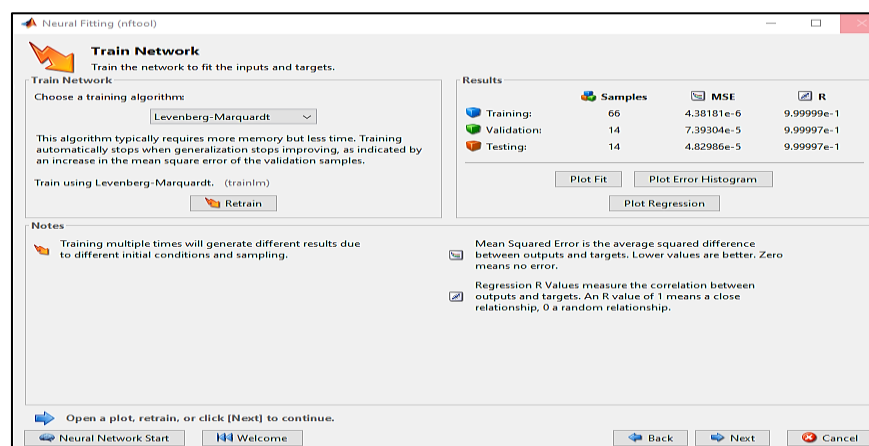


Figure III.21: Train Network

Training Results: After training, this figure shows the results, including the mean squared error (MSE) for the training, validation, and testing datasets.

Regression Plot: This plot shows the correlation between the network outputs and the targets. A high R-value close to 1 indicates a good fit.

Error Histogram: This plot shows the distribution of errors between the network outputs and the targets[22].

III.6.Conclusion :

This chapter addressed the fundamental and most critical aspects of the current study, focusing on the operational principles of Maximum Power Point Tracking (MPPT). A systematic classification of MPPT control strategies was presented, followed by a rigorous analysis of the methodologies most prevalent in the existing literature. The diversity of these control mechanisms underscores the ongoing evolution within this research field and highlights the inherent complexity of establishing a universal solution applicable to all operating conditions

Chapter IV:
Simulation
Results

IV.1.Introduction :

In this chapter, a detailed performance evaluation and comparative analysis of three widely adopted Maximum Power Point Tracking (MPPT) algorithms Perturb and Observe (P&O), Incremental Conductance (INC), and Artificial Neural Network (ANN) is presented. These algorithms play a fundamental role in enhancing the power output of photovoltaic (PV) systems by continuously regulating the operating point to achieve optimal energy extraction from solar panels. Accurate tracking of the maximum power point significantly contributes to improving system efficiency, operational reliability, and overall energy yield. The P&O algorithm operates through successive perturbations and observations to identify the optimal operating condition, whereas the INC algorithm applies the incremental conductance principle to achieve more precise adjustments under varying environmental conditions. In contrast, the ANN-based approach employs artificial intelligence techniques to predict and track the maximum power point with enhanced accuracy and adaptability. This comprehensive study aims to evaluate the advantages and limitations of each algorithm, thereby providing meaningful insights into their effectiveness and suitability across different operating scenarios.

IV.2.Parameters of System Simulation :

The following characteristics of panel and the parameters of boost converter that are used in our system simulation, are shown in the figure and table below:

Module data			
Module: User-defined			
Maximum Power (W)	200.22	Cells per module (Ncell)	60
Open circuit voltage Voc (V)	57.6	Short-circuit current Isc (A)	4.6
Voltage at maximum power point Vmp (V)	47	Current at maximum power point Imp (A)	4.26
Temperature coefficient of Voc (%/deg.C)	-0.35502	Temperature coefficient of Isc (%/deg.C)	0.06

Figure IV.1: Characteristics of Panel

Boost Converter	Value
Capacitor 1	200 μ F
Inductor	3.5 mH

Capacitor 2	100 μ F
Resistive Load	300 Ω

Table IV.1: Parameters of Boost Converter

IV.3.Simulation Results :

IV.3.1.P&O Algorithm :

In this simulation, the Perturb and Observe (P&O) algorithm was implemented to obtain the power, voltage, and current responses. Figure (IV.2) presents the overall system simulation, illustrating the general configuration and operational performance of the P&O-based MPPT system, the figure demonstrates the integration of photovoltaic (PV) panels with the P&O-based MPPT controller, which continuously regulates the duty cycle in order to ensure optimal power extraction.

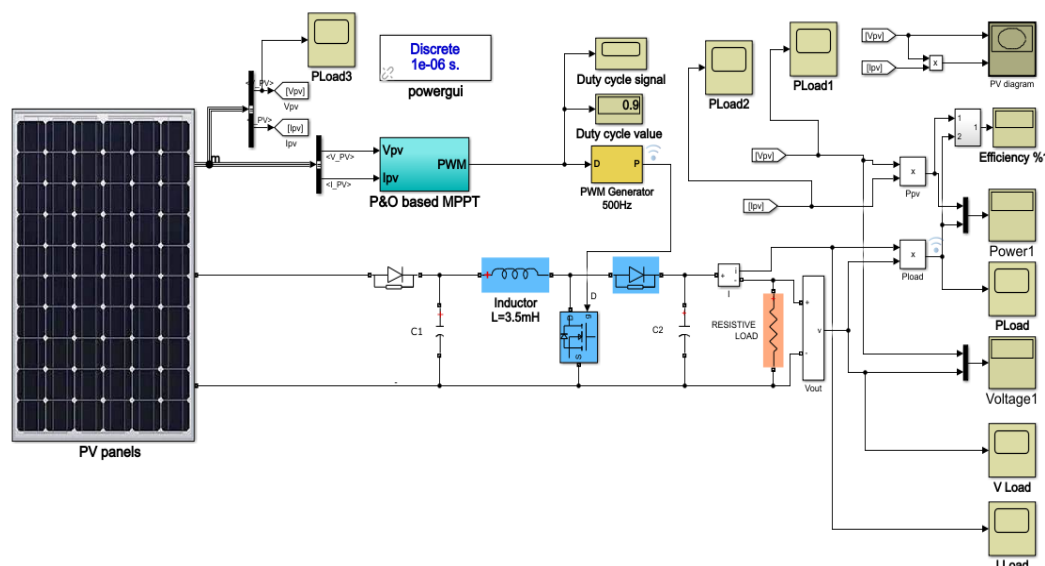


Figure IV.2: Schema of System Simulation With P&O

IV.3.1.1.Constant Irradiance (1000 W/m²) :

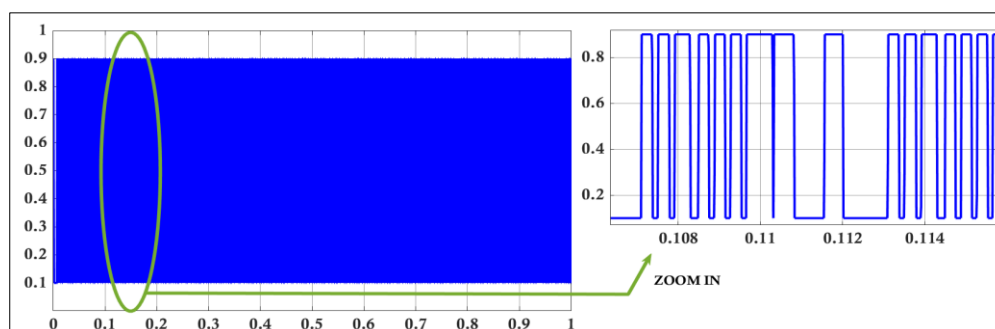


Figure IV.3: Duty Cycle Simulation Result

Figure (IV.3) illustrates the duty cycle behavior of the MPPT system, where the main plot highlights the overall system stability, while the zoomed-in view reveals the small yet significant fluctuations required for accurate MPPT operation.

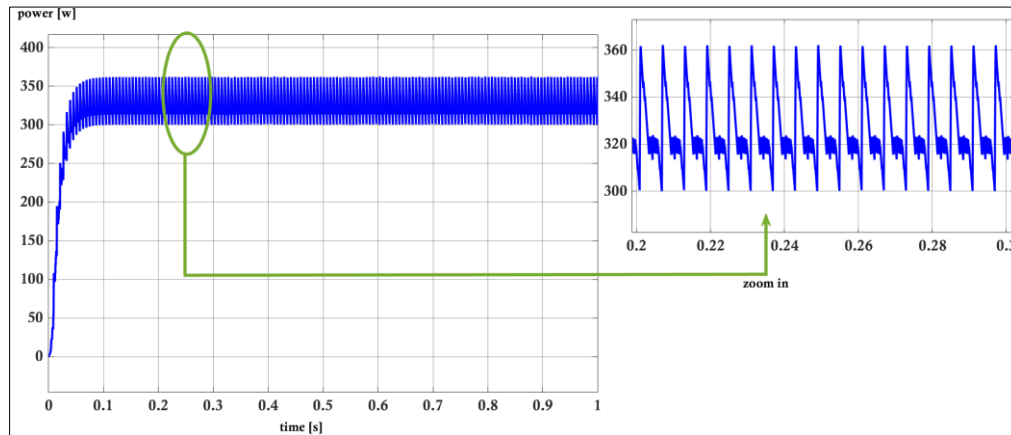


Figure IV.4: Power Simulation Result

Figure (IV.4) depicts the power response of an MPPT system employing the P&O algorithm, where the main plot indicates a rapid rise in power followed by stabilization around 350 W, while the zoomed-in view emphasizes the oscillatory behavior of the power output, these oscillations, inherent to the P&O algorithm due to its continuous perturbations for maximum power point tracking, represent a necessary trade-off to maintain optimal power extraction and are essential for evaluating the efficiency and overall performance of the MPPT system.

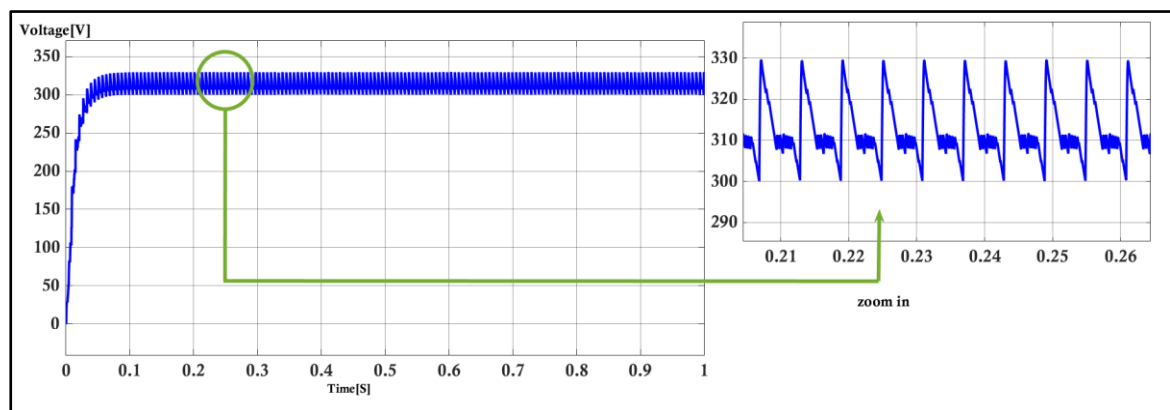


Figure IV.5: Voltage Simulation Result

Figure (IV.5) presents the voltage response of an MPPT system utilizing the P&O algorithm, where the main plot demonstrates a rapid rise in voltage, stabilizing around 320 V, while the zoomed-in view highlights the oscillatory behavior of the voltage output.

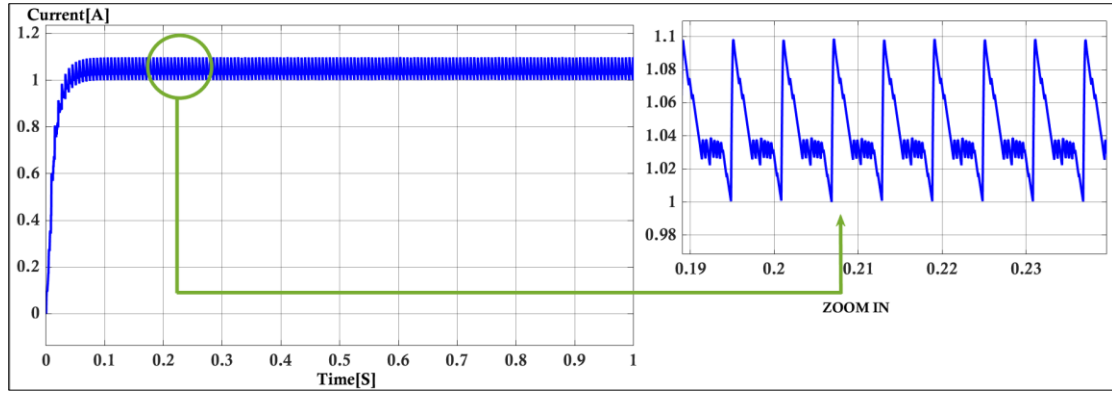


Figure IV.6: Current Simulation Result

Figure (IV.6) illustrates the current response of an MPPT system employing the P&O algorithm, where the main plot demonstrates a rapid transient response followed by stabilization at approximately 1.05 A, indicating that the system has reached its maximum power point, while the zoomed-in view offers a closer examination of the inherent oscillations around this steady-state value.

IV.3.1.2. Variable Irradiances (1000, 700, 500, 400 W/m²) :

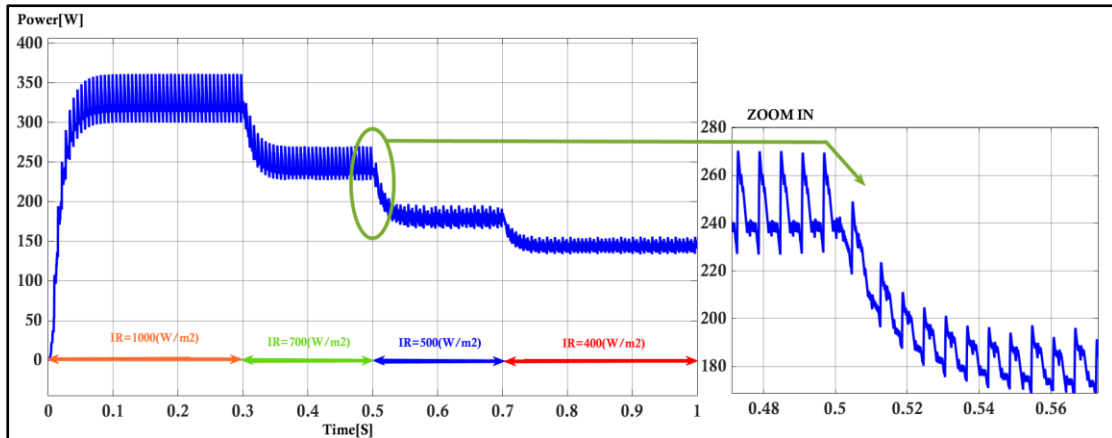


Figure IV.7: Power Simulation Result

Figure (IV.7) provides a comprehensive depiction of the power output behavior of the MPPT system under varying solar irradiance levels, where the main plot illustrates the system's capability to track the maximum power point across different irradiances, with power stabilizing at approximately 350 W, 270 W, 200 W, and 170 W for irradiance levels of 1000 W/m², 700 W/m², 500 W/m², and 400 W/m², respectively. The green ellipse and the zoomed-in view highlight the system's transient response to a sudden drop in irradiance, revealing the characteristic oscillations as the P&O algorithm

adjusts to the new maximum power point, thereby emphasizing the system's efficiency and adaptability in real-time solar energy applications.

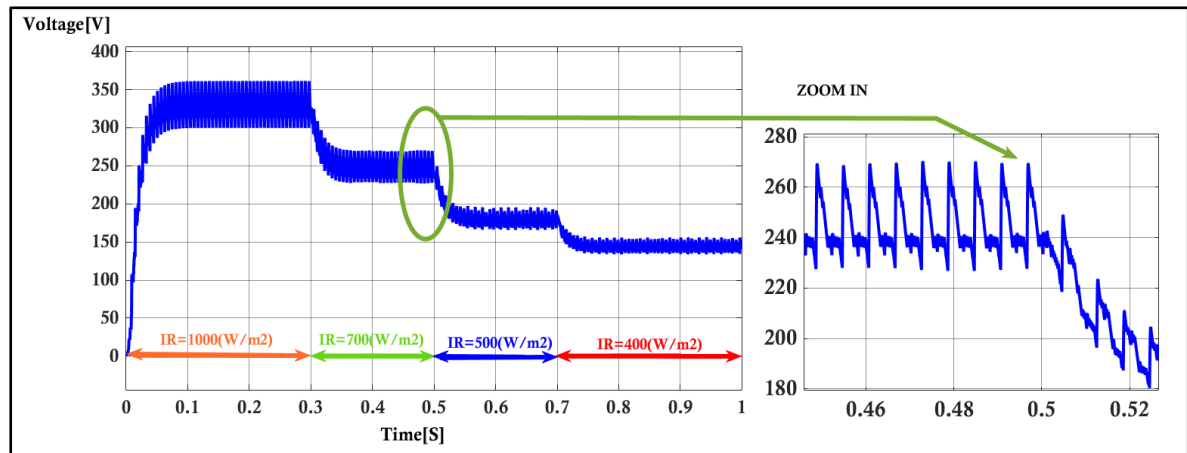


Figure IV.8: Voltage Simulation Result

Figure (IV.8) illustrates the voltage response of an MPPT system employing the P&O algorithm under varying irradiance levels, where the main plot demonstrates the system's rapid voltage stabilization around 360 V, followed by stepwise decreases corresponding to reductions in irradiance, while the zoomed-in view provides a detailed examination of the transient fluctuations.

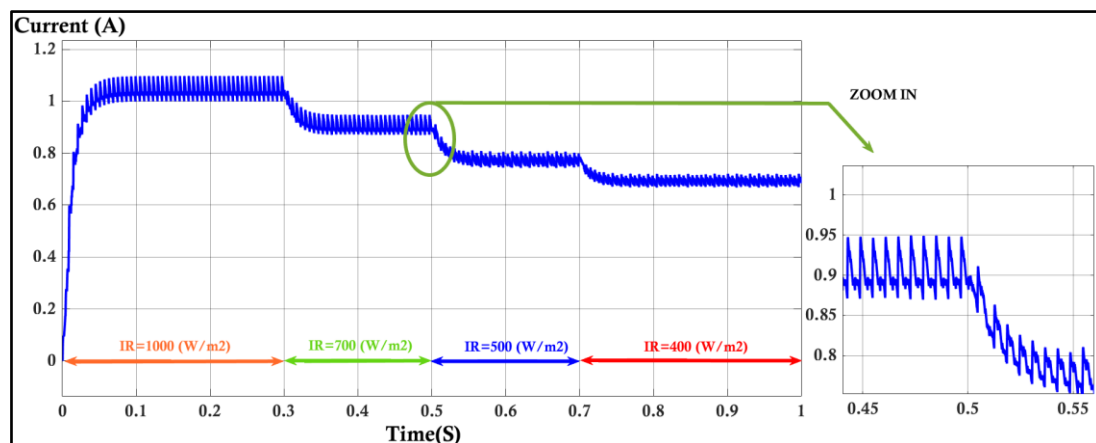


Figure IV.9: Current Simulation Result

Figure (IV.9) illustrates the current output response of an MPPT system controlled by the P&O algorithm under varying irradiance levels, where the main plot shows the current stabilizing around 1 A and decreasing in discrete steps as the irradiance diminishes, while the zoomed-in view captures the transient behavior during changes in irradiance.

IV.3.2.Incremental Conductance :

In this simulation, the Incremental Conductance (INC) algorithm was employed to obtain the power, voltage, and current responses. Figure (IV.10) presents the overall system simulation, illustrating the general configuration and operational performance of the INC-based MPPT system, while also demonstrating the integration of photovoltaic (PV) panels with the INC-based MPPT controller, which continuously adjusts the duty cycle to achieve optimal power extraction.

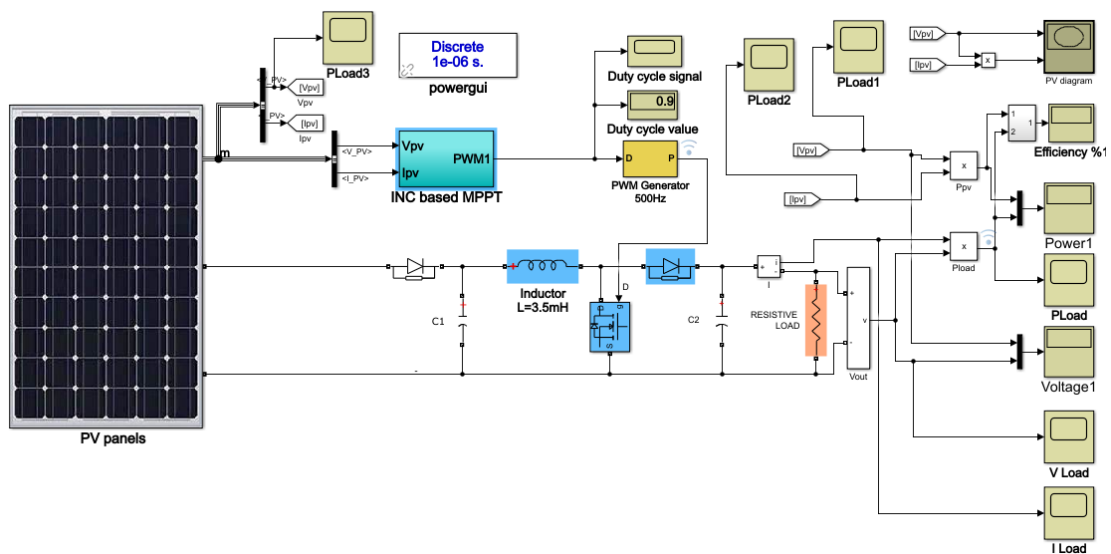


Figure IV.10: Schema of System Simulation With INC

IV.3.2.1.Constant Irradiance (1000 W/m²) :

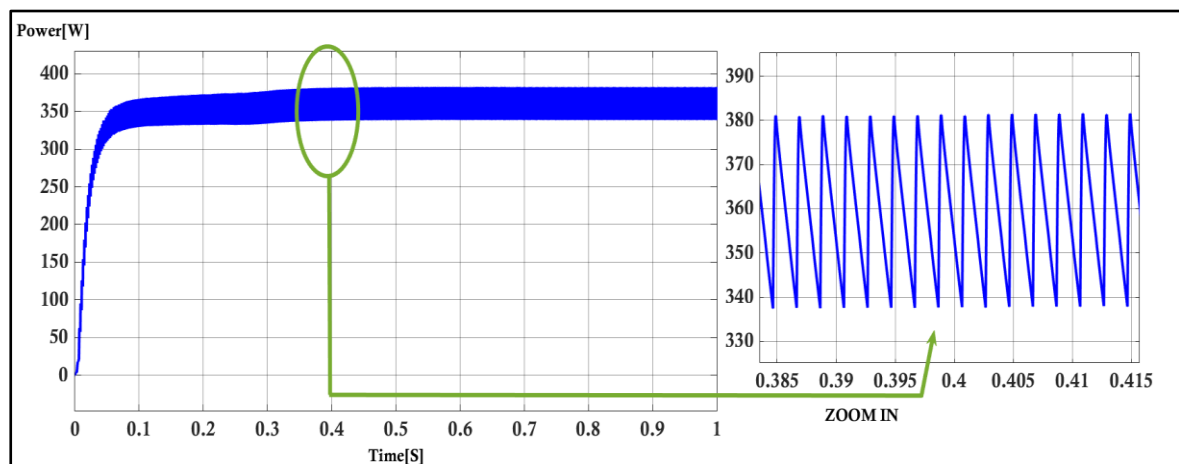


Figure IV.11: Power Simulation Result

Figure (IV.11) illustrates the power stabilization behavior of an MPPT system governed by the Incremental Conductance algorithm, where the main plot shows a rapid increase and subsequent stabilization of power around 370 W, reflecting the system's

efficiency, while the zoomed-in view highlights periodic fluctuations, demonstrating the algorithm's continuous adjustments to maintain optimal power output, this analysis emphasizes the capability of the Incremental Conductance algorithm to dynamically and accurately track the maximum power point.

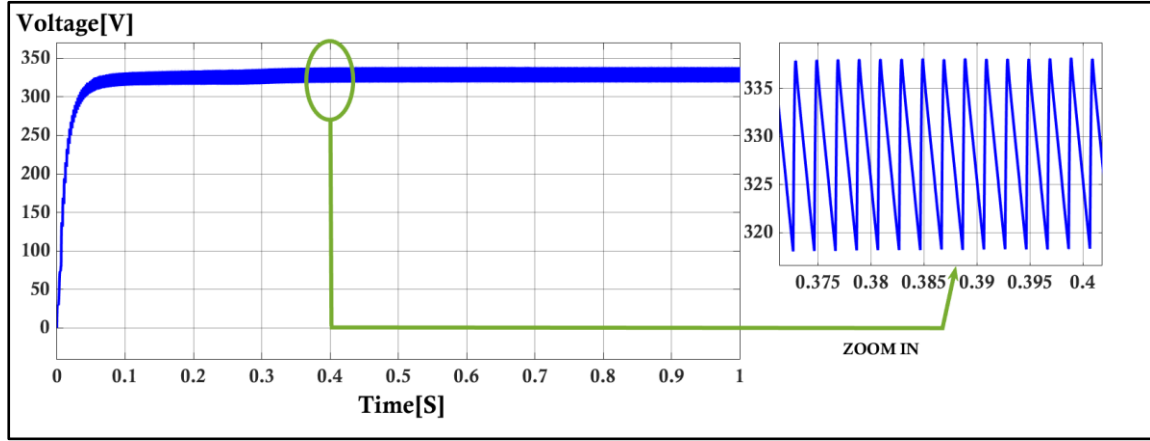


Figure IV.12: Voltage Simulation Result

Figure (IV.12) illustrates the voltage response of an MPPT system based on the Incremental Conductance algorithm, where the main plot shows the voltage stabilizing around 330 V, while the zoomed-in view captures the small transient fluctuations.

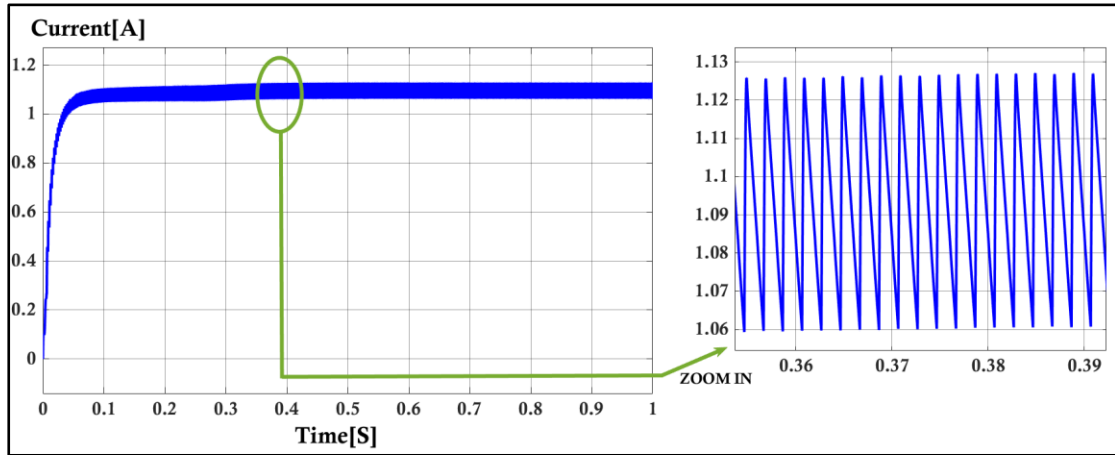


Figure IV.13: Current Simulation Result

Figure (IV.13) illustrates the current stabilization behavior of an MPPT system controlled by the Incremental Conductance algorithm, where the main plot shows the current rapidly rising and stabilizing around 1.1 A, indicating the system's efficiency in reaching the maximum power point, while the zoomed-in view highlights small fluctuations in the current.

IV.3.2.2. Variable Irradiances (1000, 700, 500, 400 W/m²) :

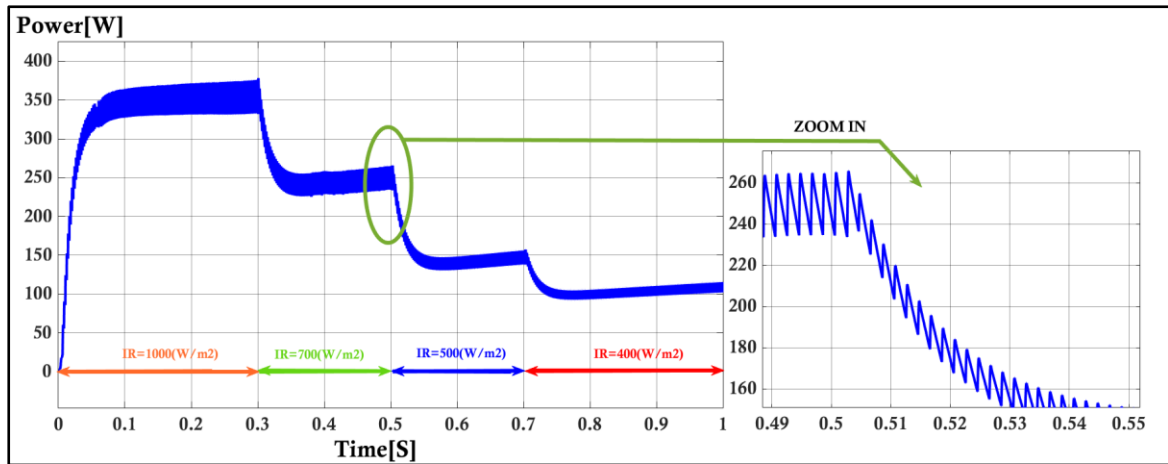


Figure IV.14: Power Simulation Result

Figure (IV.14) presents the power response of an MPPT system using the Incremental Conductance algorithm under varying irradiance conditions, where the main plot demonstrates the power initially stabilizing around 350 W, followed by discrete stepwise decreases as the irradiance declines, while the zoomed-in view captures the transient fluctuations during irradiance changes.

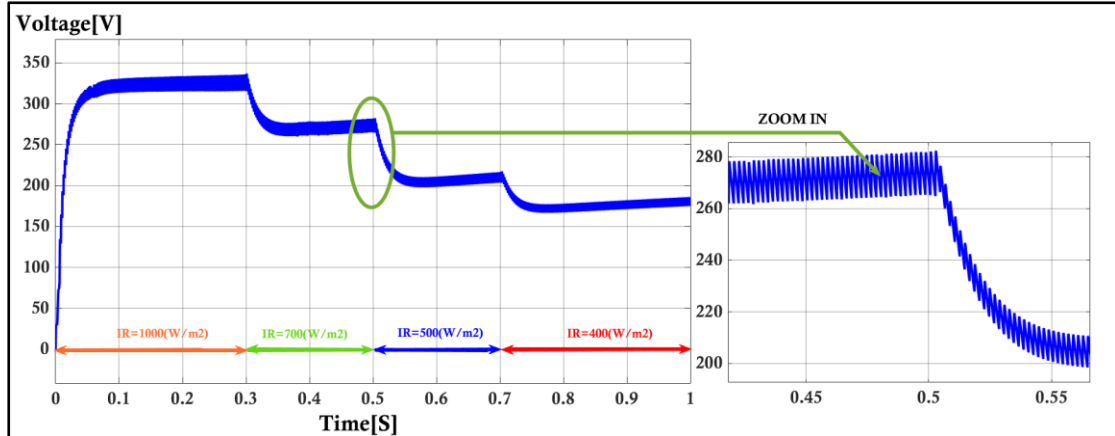


Figure IV.15: Voltage Simulation Result

Figure (IV.15) illustrates the voltage response of an MPPT system based on the Incremental Conductance algorithm under varying irradiance levels, where the main plot shows a rapid rise followed by stabilization around 330 V, with stepwise decreases corresponding to reductions in irradiance, while the zoomed-in view highlights the transient fluctuations.

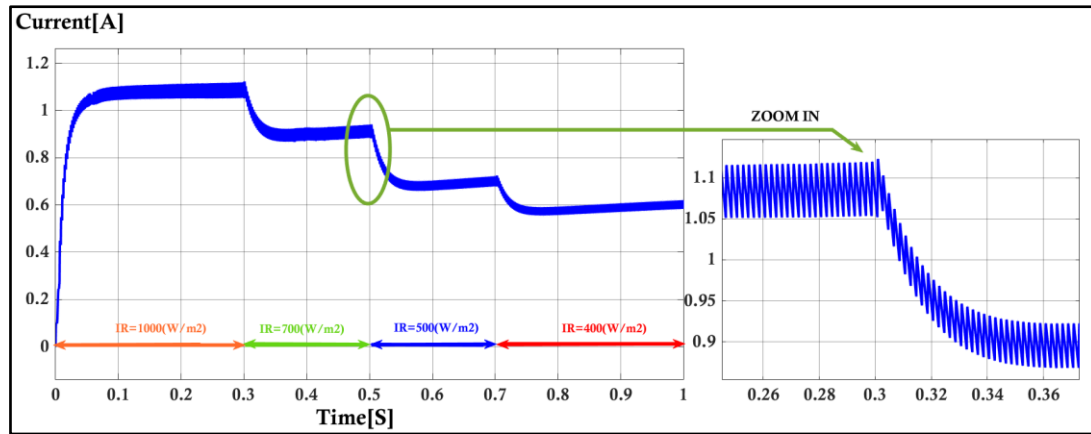


Figure IV.16: Current Simulation Result

Figure (IV.16) illustrates the current response of an MPPT system employing the Incremental Conductance algorithm under varying irradiance conditions, where the main plot shows the current initially stabilizing around 1.1 A, followed by stepwise decreases as the irradiance diminishes, while the zoomed-in view captures the transient fluctuations occurring during changes in irradiance.

IV.3.3. Artificial Neural Network (ANN) :

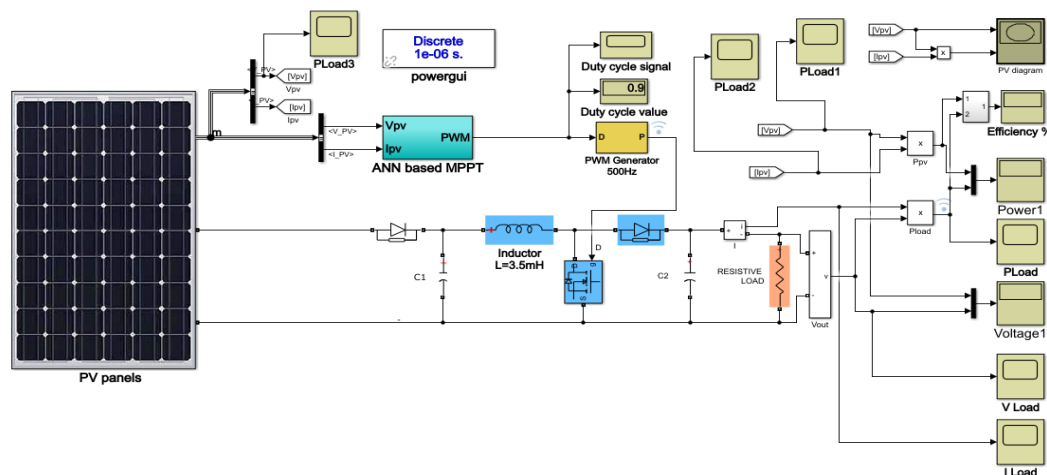


Figure IV.17: Schema of System Simulation With ANN

In this simulation, the Artificial Neural Network (ANN) algorithm was employed to obtain the power, voltage, and current responses. Figure (IV.17) presents the overall system simulation, illustrating the general configuration and operational performance of the ANN-based MPPT system, while also demonstrating the integration of photovoltaic (PV) panels with the ANN-based MPPT controller, which continuously adjusts the duty cycle to achieve optimal power extraction.

IV.3.3.1.Constant Irradiance (1000 W/m²) :

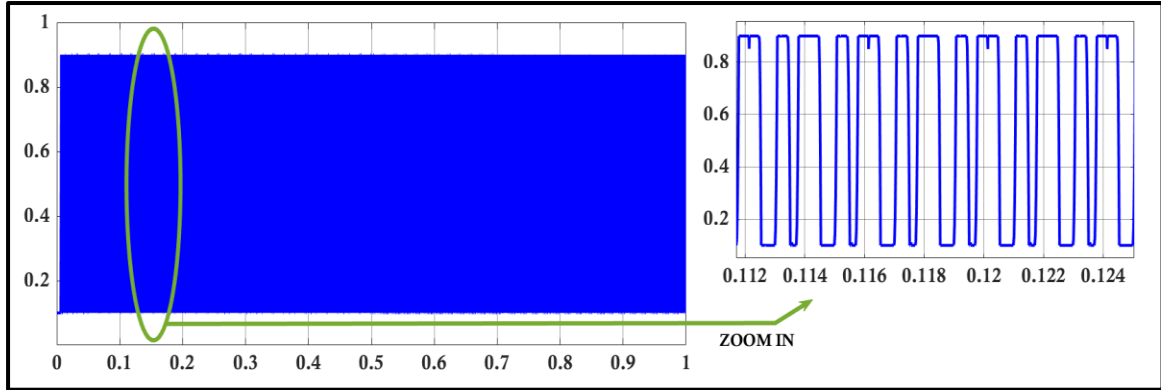


Figure IV.18: Duty Cycle Simulation Result

Figure (IV.18) illustrates the stability and fine-tuning of the duty cycle in an ANN-based MPPT system, where the main plot shows a stable duty cycle around 1, while the zoomed-in view highlights periodic adjustments.

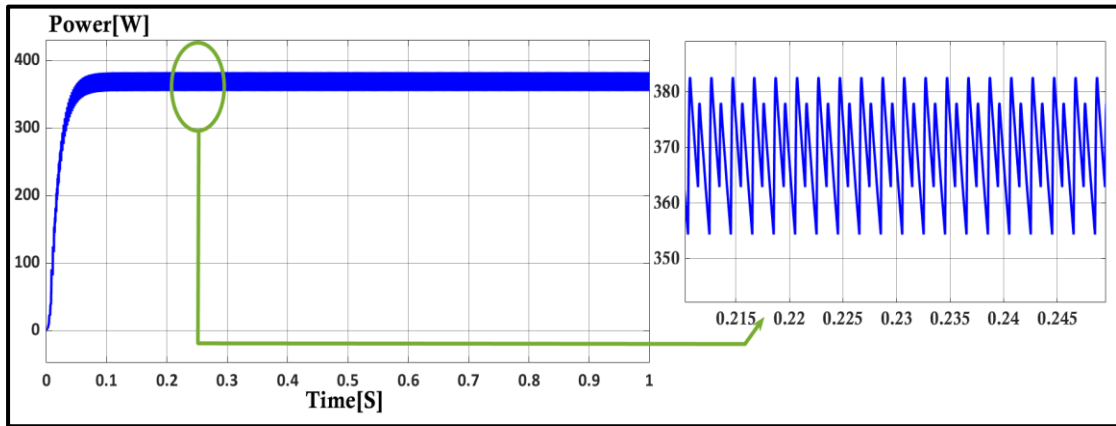


Figure IV.19: Power Simulation Result

Figure (IV.19) illustrates the power stabilization behavior of an MPPT system controlled by an ANN algorithm, where the main plot shows a rapid rise followed by stabilization of power around 380 W, reflecting the system's efficiency, while the zoomed-in view highlights periodic fluctuations, demonstrating the ANN's continuous adjustments to maintain optimal power output, this analysis emphasizes the ANN algorithm's capability to dynamically and accurately track the maximum power point.

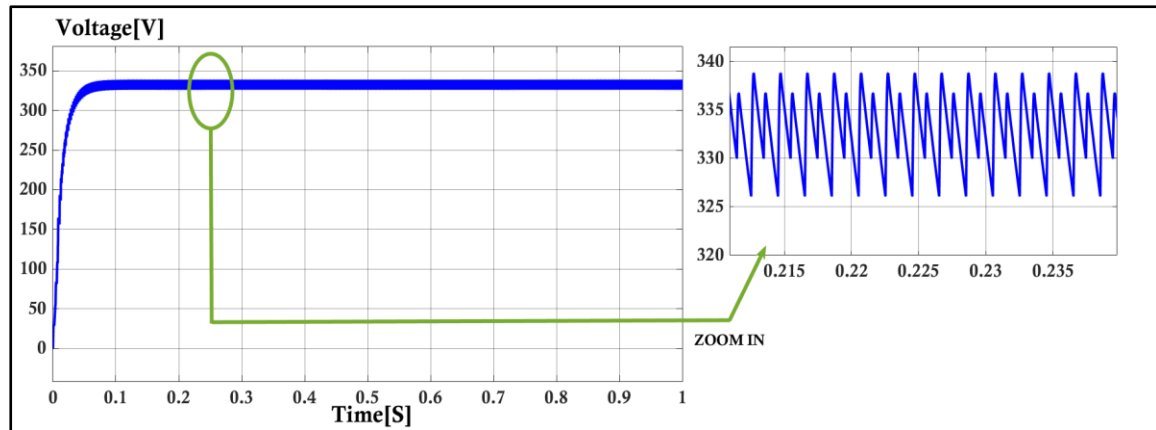


Figure IV.20 : Voltage Simulation Result

Figure (IV.20) illustrates the voltage response of an ANN-based MPPT system, where the main plot shows a rapid rise followed by stabilization around 335 V, while the zoomed-in view captures small fluctuations.

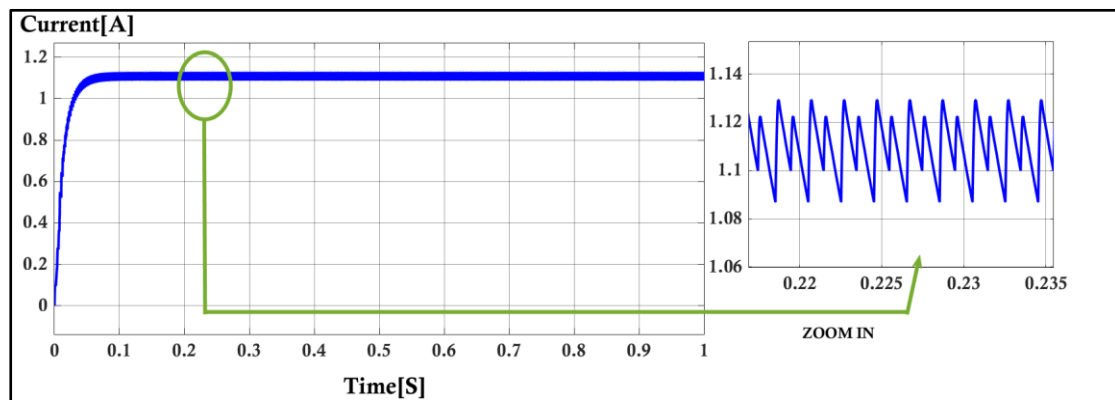


Figure IV.21: Current Simulation Result

Figure (IV.21) illustrates the current stabilization behavior of an ANN-based MPPT system, where the main plot shows a rapid rise in current followed by stabilization around 1.1 A, while the zoomed-in view highlights small fluctuations.

IV.3.3.2. Variable Irradiances (1000, 700, 500, 400 W/m²) :

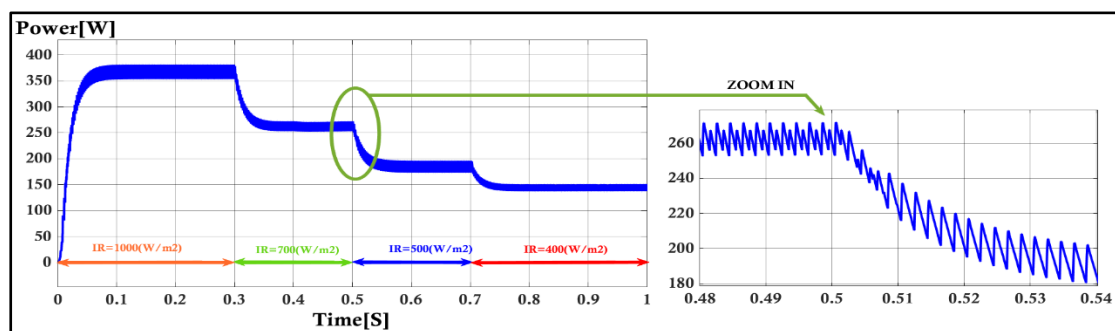


Figure IV.22: Power Simulation Result

Figure (IV.22) illustrates the power response of an ANN-based MPPT system under varying irradiance conditions, where the main plot shows the power initially stabilizing around 350 W, followed by stepwise decreases as the irradiance diminishes, while the zoomed-in view captures the transient fluctuations occurring during changes in irradiance.

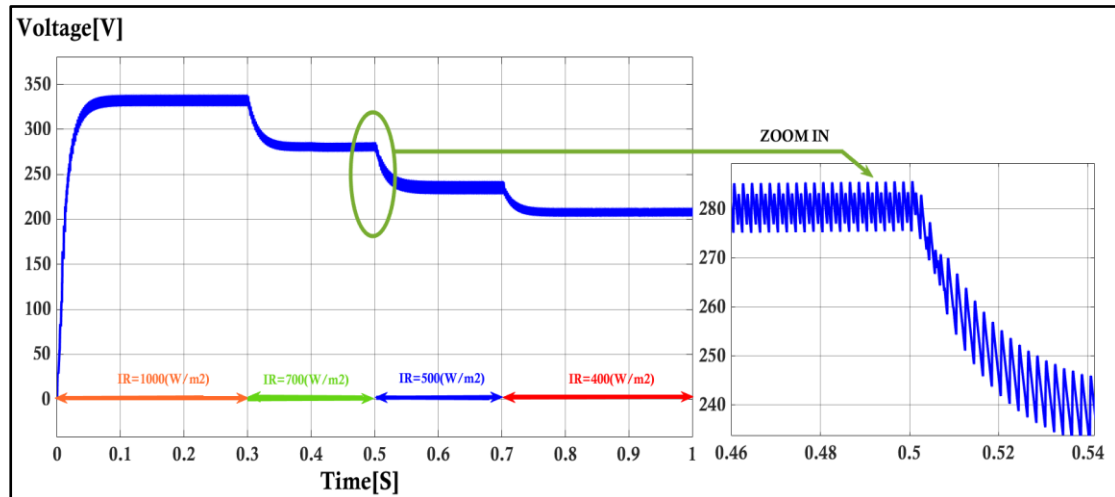


Figure IV.23: Voltage Simulation Result

Figure (IV.23) illustrates the voltage response of an ANN-based MPPT system under varying irradiance conditions, where the main plot shows the voltage stabilizing around 330 V and decreasing gradually in steps as the irradiance diminishes, while the zoomed-in view highlights the transient fluctuations..

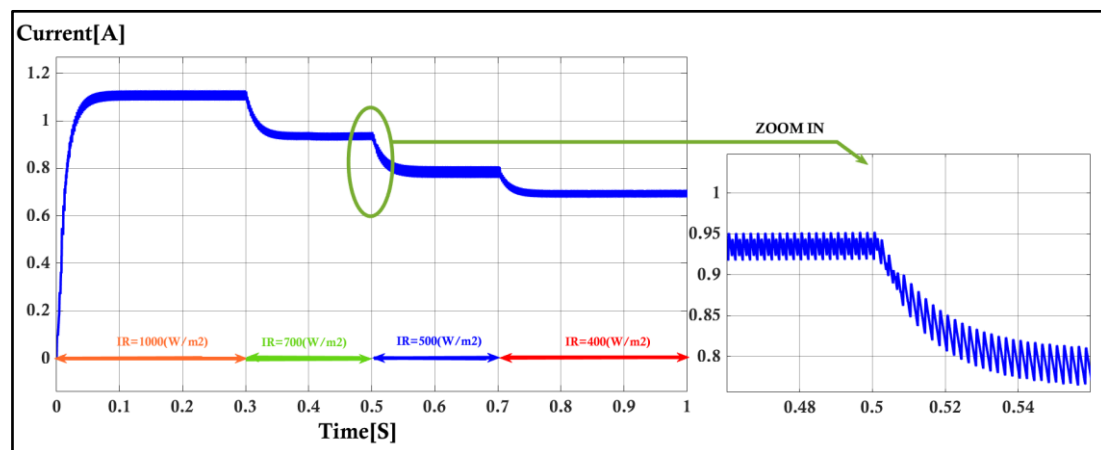


Figure IV.24: Current Simulation Result

Figure (IV.24) illustrates the current response of an ANN-based MPPT system under varying irradiance conditions, where the main plot shows the current initially stabilizing around 1.1 A, followed by stepwise decreases as the irradiance diminishes, while the

zoomed-in view captures the transient fluctuations occurring during changes in irradiance.

IV.3.4.Fuzzy Logic Control (FLC):

In this simulation, we used the Fuzzy Logic Controller (FLC) algorithm to obtain results for power, voltage, and current. Figure (IV.25) represents the general system simulation, showcasing the overall setup and performance of the FLC-based MPPT system. The figure illustrates the integration of PV panels with the FLC-based MPPT controller, which adjusts the duty cycle to optimize power extraction.

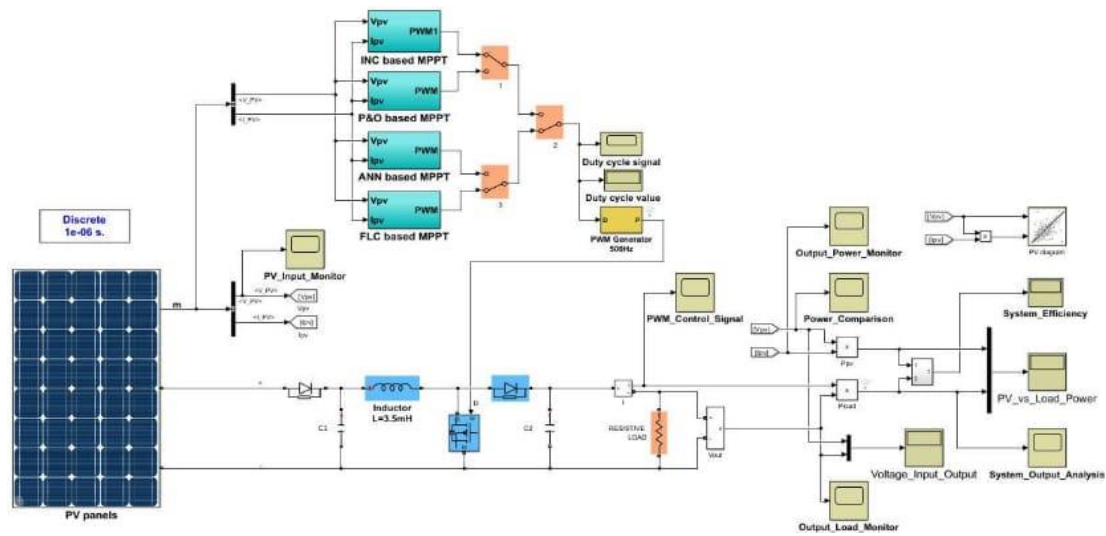


Figure IV.25: Schematic simulation system with FLC

IV.3.4.1.Constant Irradiance (1000 W/m²) :

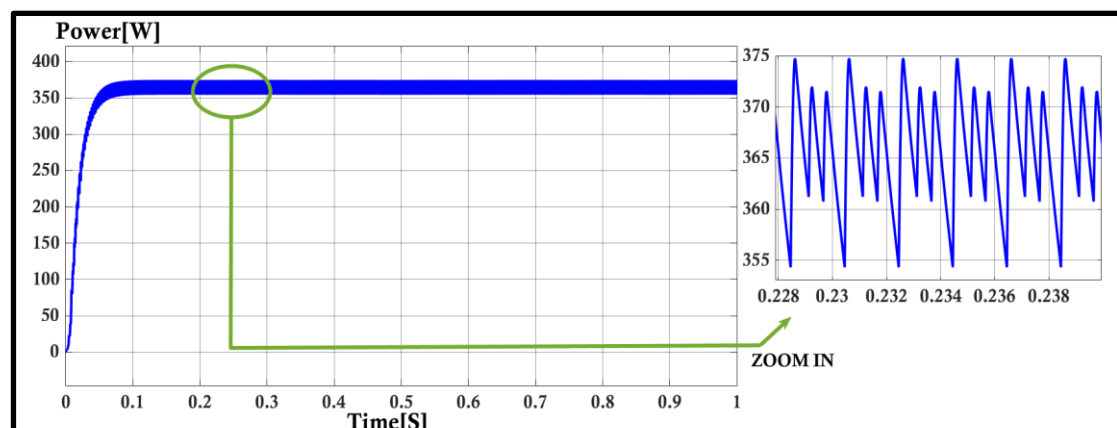


Figure IV.26: Power Simulation Result

The figure (IV.26) illustrates the system power output exponentially increasing quickly to around 370 W under constant irradiance, controlled by a Fuzzy Logic Controller (FLC). After this initial rise (transient time), the power stays fairly stable around this value but shows continuous, relatively small-scale, cyclical fluctuations (steady-state). Zooming in stresses these oscillations, suggesting natural dynamics or control reactions within the FLC-controlled system. The FLC performs well in regulating the average power, but there is a steady-state ripple.

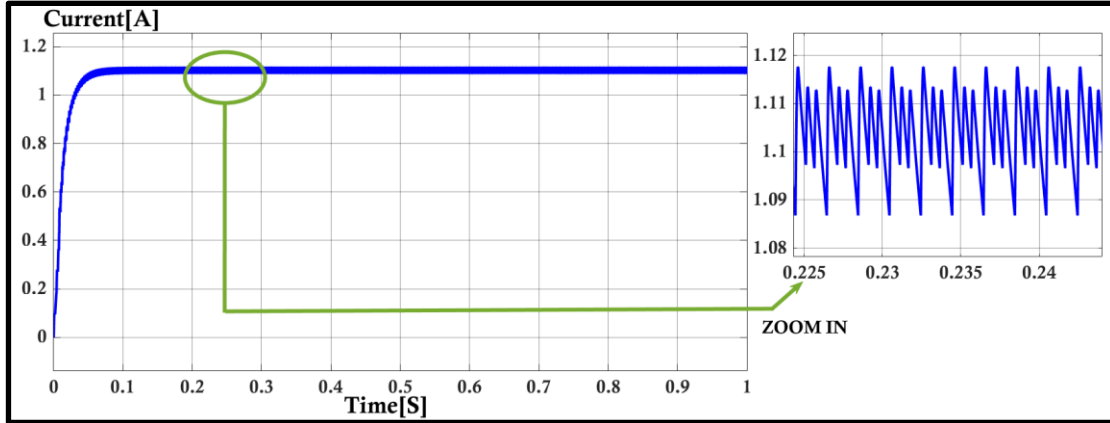


Figure IV.27: Current Simulation Result

Figure (IV.27) illustrates the current response of an MPPT system employing the P&O algorithm, where the main plot demonstrates a rapid transient response followed by stabilization at approximately 1.05 A, indicating that the system has reached its maximum power point, while the zoomed-in view offers a closer examination of the inherent oscillations around this steady-state value.

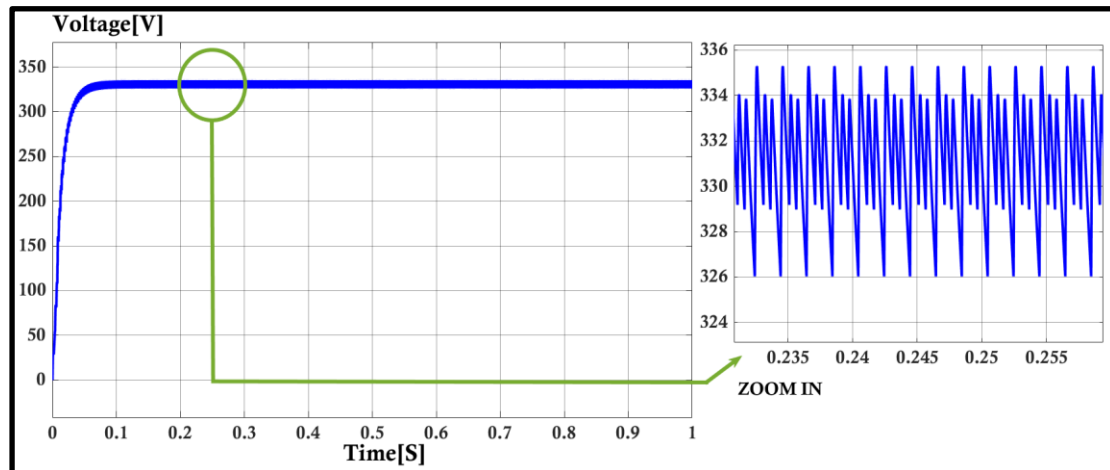


Figure IV.28: Voltage Simulation Result

The figure represents the voltage behavior of an FLC-based MPPT system under constant irradiance conditions. The curve shows a rapid rise in voltage, quickly stabilizing around a specific value (approximately 335V). This indicates the system's ability to adapt efficiently and reach

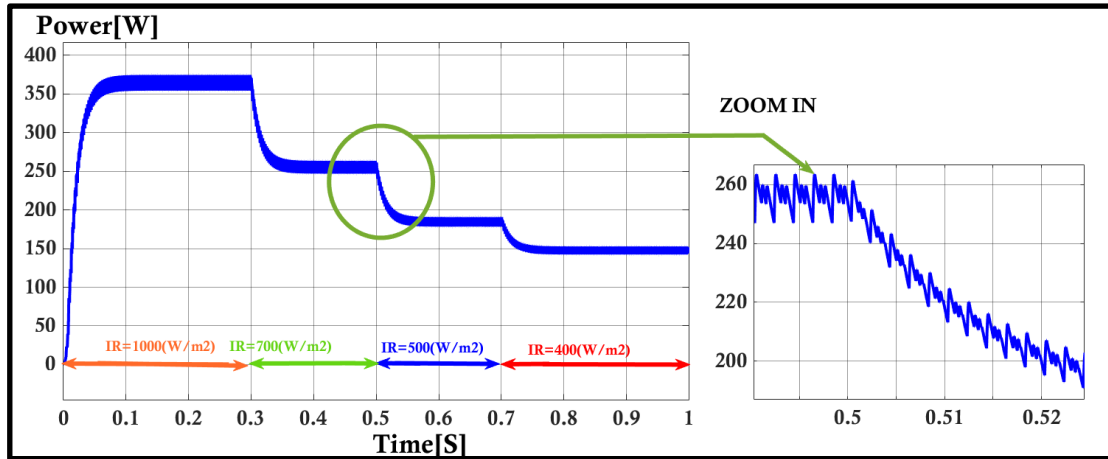
IV.3.4.2. Variable Irradiances (1000, 700, 500, 400 W/m²) :

Figure IV.29: Power Simulation Result

The figure illustrates the performance of the Fuzzy Logic Controller (FLC) based MPPT system under fluctuating irradiance conditions. Initially, the power stabilizes at approximately 350W, followed by stepwise decreases as irradiance levels drop over time. The zoomed-in section highlights transient fluctuations during these transitions, with power briefly oscillating between 340W and 350W before stabilizing at a new level. These precise adjustments demonstrate the system's ability to dynamically adapt to rapid changes in irradiance while maintaining efficient energy extraction.

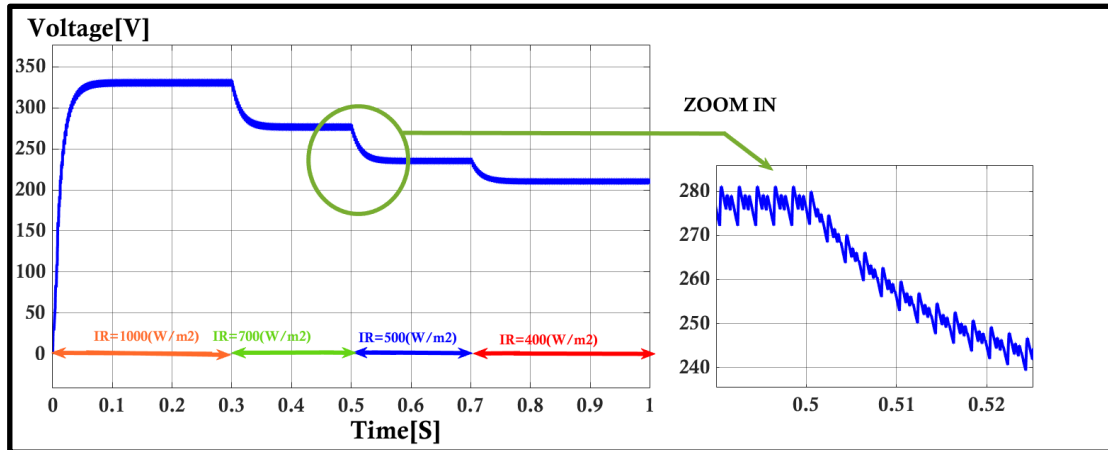


Figure IV.30: Voltage Simulation Result

The Figure (IV.29) illustrates the FLC-based MPPT system's voltage response to varying irradiance. The main plot shows the voltage stabilizing around 330V and stepping down to approximately 250-270V with decreasing irradiance. The zoomed-in view reveals minor transient fluctuations during adaptation. Each stabilization period after irradiance changes takes approximately 0.02 to 0.05 seconds. This demonstrates the FLC algorithm's ability to efficiently adapt to dynamic solar irradiance changes while maintaining stable performance.

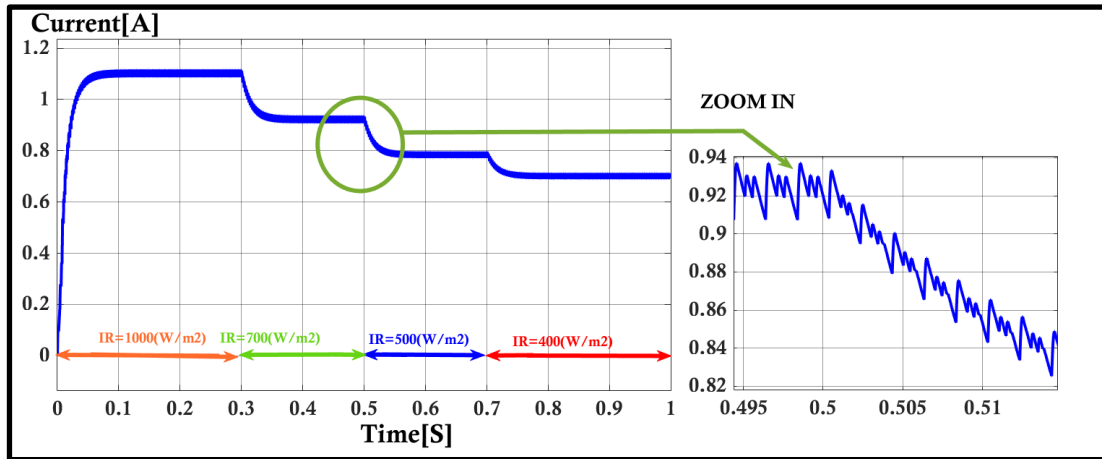


Figure IV.31: Current Simulation Result

The figure (IV.30) depicts the current response of an FLC-based MPPT system under fluctuating irradiance levels. Initially, the current stabilizes at approximately 1.1A, showing steady behaviour. As irradiance decreases, the current exhibits stepwise reductions, reaching around 0.8A during lower irradiance periods. The zoomed-in section highlights transient fluctuations, with minor oscillations of about $\pm 0.05A$, reflecting the system's dynamic adaptation to rapid changes in irradiance.

IV.4.Comparison and Analysis Between (P&O, INC, ANN,FLC) :

IV.4.1. Constant Irradiance (1000 W/m²):

The following figures present a comparative analysis of the current and voltage outputs for four MPPT algorithms: Incremental Conductance (INC), Perturb and Observe (P&O), Artificial Neural Network (ANN), and Fuzzy Logic Control (FLC).

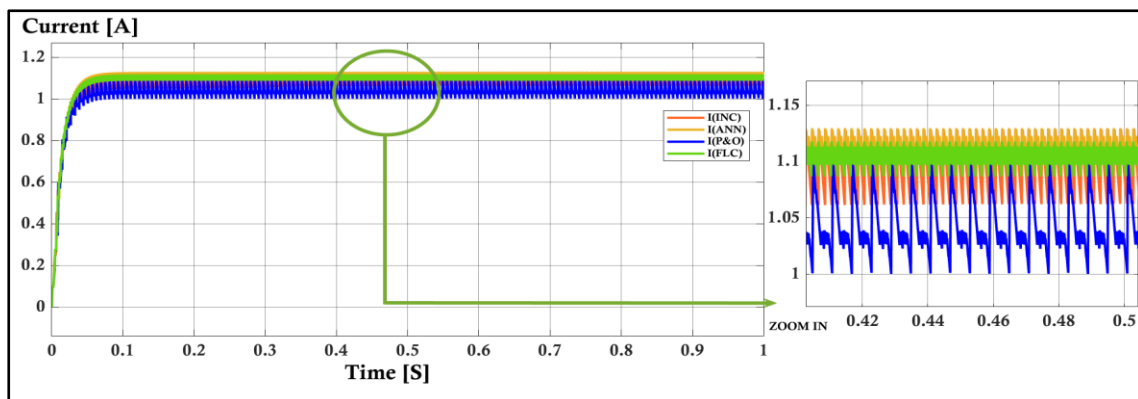


Figure IV.32: Current Simulation Result

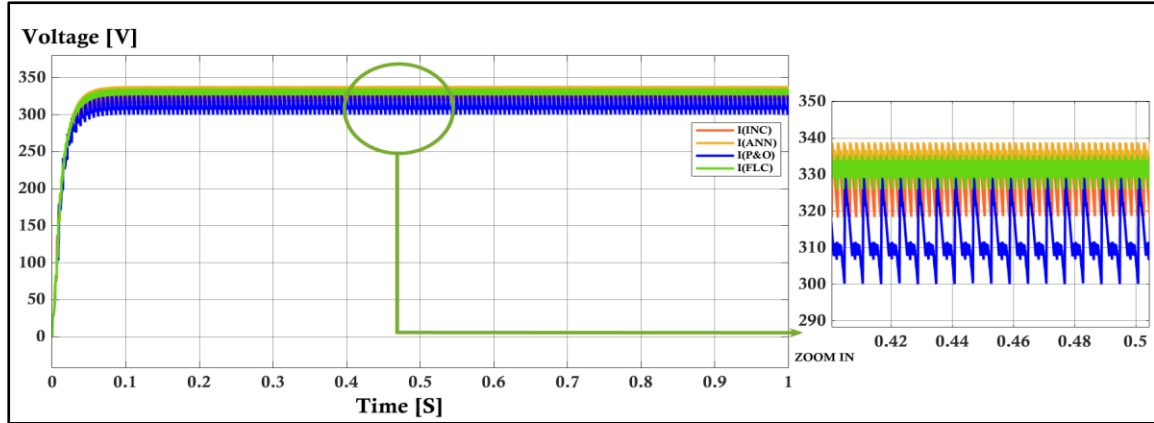


Figure IV.33: Voltage Simulation Result

IV.4.1.1. Comparison :

- **Incremental Conductance (INC):** This algorithm demonstrates rapid stabilization in both current and voltage, with minimal fluctuations, reflecting efficient and stable system performance.
- **Perturb and Observe (P&O):** Although it achieves rapid stabilization, it exhibits higher fluctuations in both current and voltage, indicating relatively lower stability compared to the other algorithms.
- **Fuzzy Logic Controller (FLC):** This algorithm provides a very fast response with high precision and near-zero oscillations around the maximum power point (MPP), even under rapidly changing atmospheric conditions.
- **Artificial Neural Network (ANN):** This algorithm attains stabilization with minimal fluctuations, comparable to INC, suggesting efficient and stable performance under the given operating conditions.

IV.4.1.2. Analysis:

- **Best Performance:** FLC, ANN, and INC exhibit superior performance with minimal fluctuations. However, FLC and ANN stand out due to their ability to handle the non-linear characteristics of the PV system more effectively than the classical INC.
- **Slight Edge:** The ANN and FLC algorithms possess a significant advantage over INC and P&O due to their intelligent and adaptive nature. While ANN excels in pattern recognition, FLC is highly robust and does not require a precise mathematical model of the system.

Therefore, based on these observations, the Artificial Neural Network (ANN) and Fuzzy Logic Controller (FLC) appear to be the most effective choices for MPPT, offering the highest efficiency and fastest stabilization with negligible fluctuations, followed by the Incremental Conductance (INC) algorithm.

IV.4.1.3. Comparison General :

- **Current Comparison Table :**

Peak Current	Fluctuations	Steady-State Current	Initial Response	Method
~1.05 A	moderate	~1.05 A	Smooth, moderate	I (P&O)
~1.1 A	High	~1.1 A	Rapid, with oscillations	I (INC)
~1.12 A	Minimal	~1.12 A	Fastest and Smooth	I (ANN)
~1.12 A	Slight	~1.12 A	Fastest and Stable	I (FLC)

Table IV.2: Current Comparison

- **Voltage Comparison Table :**

Peak Current	Fluctuations	Steady-State Current	Initial Response	Method
~310 A	moderate	~310 A	Smooth, moderate	V (P&O)
~330 A	High	~330 A	Rapid, with oscillations	V (INC)
~340 A	Minimal	~340 A	Fastest and Smooth	V (ANN)

~340 A	Slight	~340 A	astest and Stable	V (FLC)
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Table IV.3: Voltage Comparison

- Adaptation to Changing Irradiance Table (Voltage & Current):

Fluctuations	Steady-State Status	Adaptation to Changing Irradiance	Initial Response	Method
Minimal / Slight	Stable	Fastest adaptation with minimal oscillations	Fastest	P(ANN / FLC)
High	Stable	Moderate adaptation with oscillations	Rapid	P (INC)
Moderate	Stable	Slow adaptation with overshoot/undershoot	Moderate	P (P&O)

Table IV.4: Adaptation to Changing Irradiance (Voltage & Current)

IV.4.2. Variable Irradiances (1000, 700, 500, 400 W/m²) :

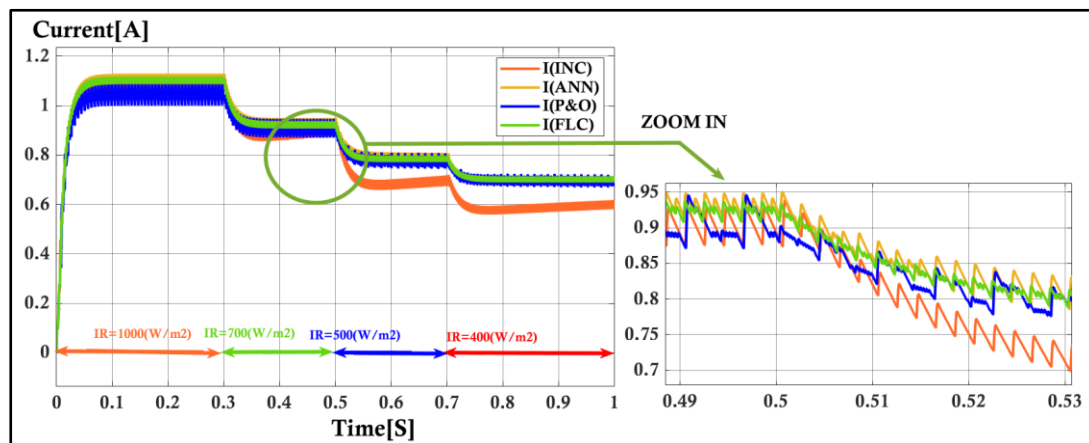


Figure IV.34: Current Simulation Result

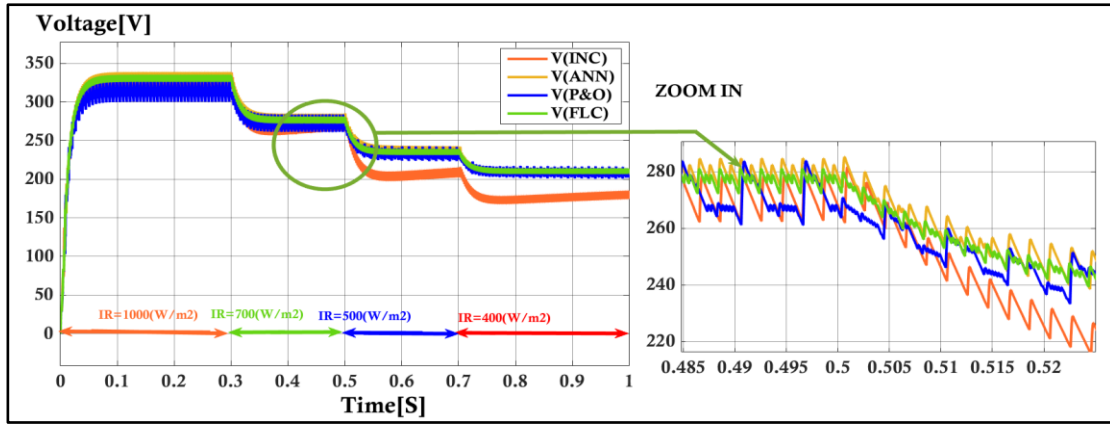


Figure IV.35: Voltage Simulation Result

IV.4.2.1.Comparison :

- **Incremental Conductance (INC)** : This algorithm demonstrates rapid stabilization; however, it exhibits visible deviations and fluctuations during changes in irradiance, indicating relatively lower stability compared to intelligent algorithms.
- **Perturb and Observe (P&O)** : This algorithm shows pronounced fluctuations and reduced stability, especially during transitions between different irradiance levels, as seen in the high-frequency oscillations in both voltage and current plots.
- **Artificial Neural Network (ANN)** : Artificial Neural Network (ANN): This algorithm exhibits the minimal fluctuations and the smoothest transitions during irradiance changes. It maintains the highest level of stability and efficiency among the compared algorithms.
- **Fuzzy Logic Controller (FLC)**: This algorithm provides a very high tracking speed with a smooth response. It effectively minimizes the steady-state oscillations, maintaining a stable output even during sharp irradiance transitions.

IV.4.2.2.Analysis :

- **Best Performance:** The Artificial Neural Network (ANN) and Fuzzy Logic Controller (FLC) algorithms demonstrate superior performance, exhibiting minimal fluctuations and smooth transitions under varying irradiance levels, which indicates enhanced stability and efficiency.
- **Slight Edge:** The ANN and FLC algorithms possess a significant advantage over the Incremental Conductance (INC) and Perturb and Observe (P&O) algorithms

due to their adaptive characteristics and improved optimization under dynamic conditions.

algorithm emerges as the most suitable choice for MPPT, providing the highest stability and efficiency under varying irradiance conditions.

IV.5. Comparison of efficiency between algorithms (P&O, INC, ANN) :

IV.5.1. Constant Irradiance (1000 W/m²) :

Algorithm	Efficiency
Perturb and Observe (P&O)	94.72%
Incremental Conductance (INC)	95.58%
Artificial Neural Network (ANN)	96.63%
Fuzzy Logic Controller (FLC)	93.18%

Table IV.5: Table of Efficiency

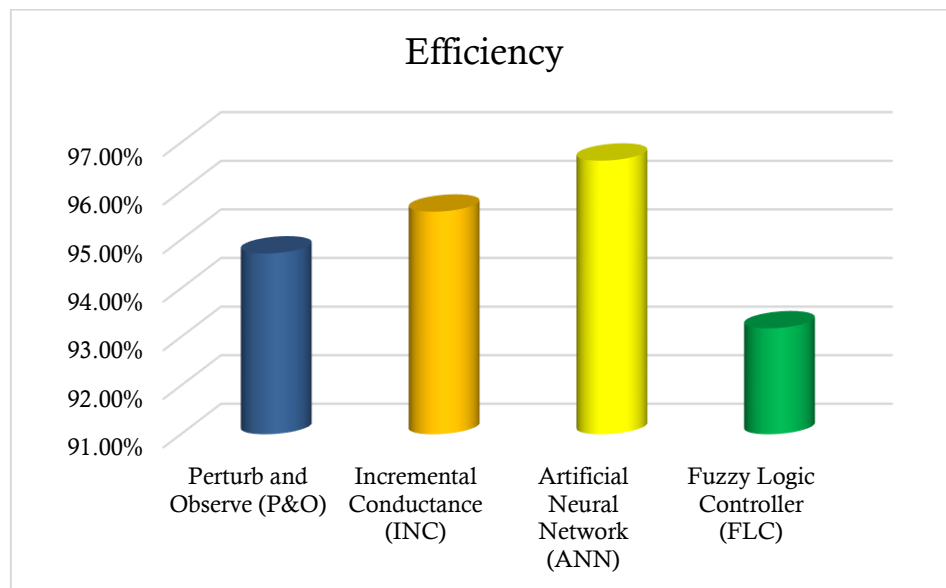


Figure IV.36: Chart of Efficiency

Under a constant irradiance of 1000 W/m^2 , the Artificial Neural Network (ANN) algorithm exhibits the highest efficiency, approximately 96.63%, followed by the Incremental Conductance (INC) algorithm with an efficiency of around 95.58%, and the Perturb and Observe (P&O) algorithm at approximately 94.72%, while the Fuzzy Logic Controller (FLC) shows an efficiency of approximately 93.18%. These results indicate that the ANN algorithm is the most effective in optimizing power output under stable irradiance conditions, surpassing the INC, P&O, and FLC algorithms in performance.

IV.5.2. Variable Irradiances (1000, 800, 600, 400 W/m^2):

Algorithm	Efficiency
Perturb and Observe (P&O)	84.84%
Incremental Conductance (INC)	88.04%
Artificial Neural Network (ANN)	95.06%
Fuzzy Logic Controller (FLC)	91.79%

Table IV.6: Table of Efficiency

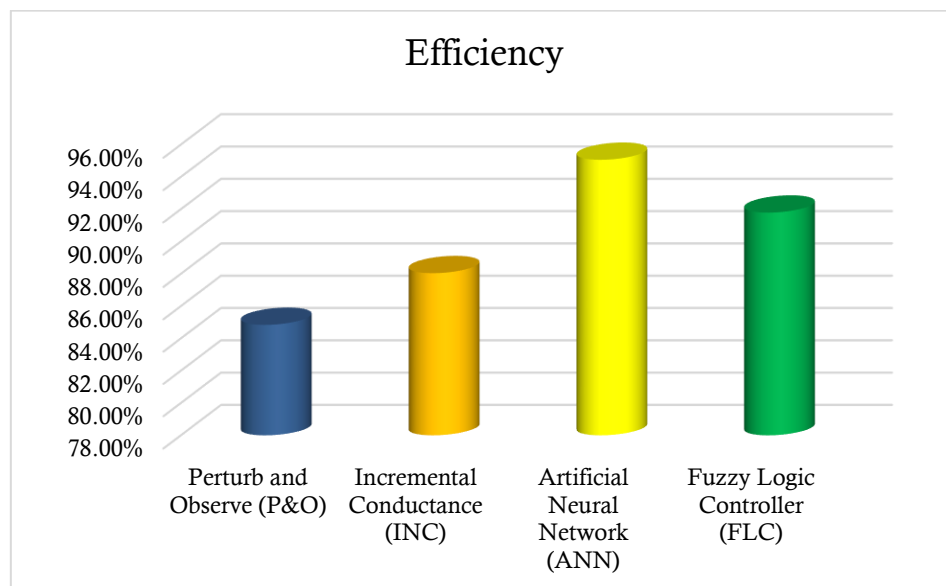


Figure IV.37: Chart of Efficiency

Under variable irradiance conditions, the Artificial Neural Network (ANN) algorithm exhibits the highest efficiency, approximately 95.06%, reflecting its superior capability to adapt to changing light conditions. The Fuzzy Logic Controller (FLC) follows with an efficiency of about 91.79%, demonstrating a high level of robustness

under dynamic environments. The Incremental Conductance (INC) algorithm shows an efficiency of around 88.04%, demonstrating reasonable performance, albeit with lower stability compared to the ANN. The Perturb and Observe (P&O) algorithm shows the lowest efficiency at around 84.84%, indicating greater susceptibility to fluctuations under varying irradiance levels. These results underscore the ANN algorithm's effectiveness in optimizing power output in dynamic environmental conditions, surpassing the FLC, INC, and P&O algorithms.

IV.6. Conclusion :

The Artificial Neural Network (ANN) algorithm emerges as the most effective and reliable MPPT method in this study, exhibiting superior efficiency, stability, and adaptability under both steady and dynamic irradiance conditions, thereby making it the optimal choice for maximizing photovoltaic system output. The Incremental Conductance (INC) algorithm, although performing better than the Perturb and Observe (P&O) algorithm, remains less capable than ANN in terms of advanced dynamic tracking and overall performance. Despite its widespread use, the P&O algorithm demonstrates the lowest effectiveness in this comparison, with reduced efficiency and greater susceptibility to instability. Consequently, for maximizing energy extraction and ensuring reliable system performance, the ANN algorithm is recommended as the preferred MPPT method.

**General
Conclusion**

General Conclusion

This study commenced by establishing a foundational understanding of solar radiation and the principles of photovoltaic energy conversion. It detailed how solar cells exploit the photovoltaic effect to generate electricity from sunlight, and examined the modeling, characteristics, and factors affecting the efficiency of photovoltaic generators, additionally, different types of photovoltaic cells based on silicon crystal structures were presented.

Building upon this foundation, the essential role of DC-DC converters in power management systems was analyzed, these converters enable efficient voltage conversion through various topologies, including buck, boost, and buck-boost, facilitating their extensive application across diverse industrial sectors.

Subsequently, the concept of Maximum Power Point Tracking (MPPT) was introduced as a critical technology, particularly for renewable energy systems such as solar power installations, MPPT algorithms enhance energy extraction by continuously adjusting the electrical operating point to track the maximum power output of photovoltaic panels.

This framework naturally led to a detailed investigation of MPPT principles, classifications, and implementation strategies, Among the MPPT algorithms evaluated, the Artificial Neural Network (ANN) approach demonstrated the highest effectiveness and reliability, its superior efficiency, stability, and adaptability under both steady and dynamic irradiance conditions establish it as the preferred method for maximizing energy extraction and ensuring robust performance in photovoltaic systems.

While other algorithms, such as Incremental Conductance (INC), showed better performance than the widely used Perturb and Observe (P&O) method, they remained less capable than ANN in achieving advanced dynamic tracking and overall performance, therefore, for optimizing photovoltaic system output and ensuring long-term, reliable operation, the ANN-based MPPT algorithm emerges as the optimal solution among the methods studied.

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