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DEDICATION

In the name of Allah, the Most Gracious, the Most
Merciful,
To the one whose prayers were the secret of my success and
the light of my path... my beloved mother,
And to the one who taught me patience and perseverance...
my dear father,
To everyone who supported me with a kind word, a sincere
prayer, or a hopeful smile,
To my respected teachers who illuminated my path with
knowledge and guidance,
To my friends who stood by me in times of difficulty,
And to everyone who carries in their heart a love for
knowledge and the pursuit of success,
I dedicate the fruit of this humble effort, hoping that Allah
makes it beneficial knowledge and a step toward a better future.
A special dedication to myself... who endured, struggled, and
never gave up,
To every moment of weakness I overcame, and every dream I
held onto until it became reality.
All praise is due to Allah, at the beginning and at the end.

Student: Atallah Abdesatar

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With deep gratitude and appreciation, I dedicate this humble
work:

To my beloved parents, who have always been my
constant support and source of strength. Without their endless
encouragement and sacrifices, I would not have reached this stage.

To my dear family, for their love, patience, and continuous
encouragement throughout my academic journey.

To my respected teachers, who have enlightened my
path with knowledge and guidance, and have been true examples
of dedication and sincerity.

To everyone who contributed, directly or indirectly, to the
accomplishment of this work.

I dedicate to you the fruit of my efforts, hoping it marks a
step toward a better future.

Student: Hamidani Nadhir

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All praise is due to Allah, by whose grace this work has been
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With great pride and gratitude, I dedicate this work:

To my beloved parents, may Allah protect them and grant
them good health,

in appreciation of their sacrifices, endless love, and constant
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Resume:

Les systèmes photovoltaïques constituent l'une des technologies les plus importantes dans le domaine des énergies renouvelables grâce à leur capacité à produire une électricité propre et durable. Toutefois, leurs performances sont fortement influencées par les variations de l'irradiation solaire et de la température, ce qui entraîne des fluctuations de la puissance produite. Dans ce contexte, ce mémoire présente une étude des systèmes photovoltaïques, des convertisseurs à courant continu, ainsi que des techniques de suivi du point de puissance maximale afin d'améliorer l'extraction de l'énergie. Il traite également des convertisseurs abaisseur, élévateur et abaisseur-élévateur, ainsi que des principales méthodes de suivi du point de puissance maximale, notamment la méthode de perturbation et observation, la méthode de la conductance incrémentale, les réseaux de neurones artificiels et la logique floue. Enfin, le système photovoltaïque a été modélisé et simulé à l'aide de MATLAB/Simulink afin d'évaluer les performances de la technique de suivi retenue. Les résultats de simulation ont montré que cette technique permet de suivre efficacement le point de puissance maximale, d'améliorer la puissance extraite et d'augmenter le rendement ainsi que la stabilité du système dans différentes conditions de fonctionnement.

Mots-clés: Conversion d'énergie – Modélisation – Optimisation – MPPT.

Abstract

Photovoltaic (PV) systems have become one of the most important renewable energy technologies for sustainable electricity generation. However, their performance is significantly affected by variations in solar irradiance and temperature. To improve energy extraction, DC-DC converters and Maximum Power Point Tracking (MPPT) techniques are employed. This dissertation presents the fundamentals of photovoltaic systems, DC-DC converters, and MPPT techniques. It also discusses the Buck, Boost, and Buck-Boost converters, as well as the Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Networks (ANN), and Fuzzy Logic Control (FLC) algorithms. The proposed photovoltaic system is modeled and simulated using MATLAB/Simulink to evaluate the performance of the selected MPPT technique. The simulation results demonstrate that the adopted MPPT technique effectively tracks the maximum power point, improves the extracted output power, and enhances the overall efficiency and stability of the photovoltaic system under varying environmental conditions.

Keywords: Energy conversion – Modeling – Optimization – MPPT.

الملخص

تُعد الأنظمة الكهروضوئية من أهم تقنيات الطاقة المتجددة لما تتميز به من قدرة على إنتاج طاقة كهربائية نظيفة ومستدامة، إلا أن أدائها يتأثر بشكل مباشر بتغير الإشعاع الشمسي ودرجة الحرارة، مما يؤدي إلى تغير القدرة الكهربائية المستخرجة. لذلك، تهدف هذه المذكرة إلى دراسة الأنظمة الكهروضوئية، ومحولات التيار المستمر، وتقنيات تتبع نقطة القدرة العظمى بهدف تحسين كفاءة استخراج الطاقة. كما تتناول دراسة محولات خفض الجهد، ورفع الجهد، والخفض والرفع، إضافة إلى استعراض أهم خوارزميات تتبع نقطة القدرة العظمى، وهي خوارزمية الاضطراب والملاحظة، وخوارزمية التوصيلية التزايدية، وخوارزمية الشبكات العصبية الاصطناعية، وخوارزمية المنطق الضبابي. وقد تم نمذجة النظام الكهروضوئي ومحاكاته باستخدام برنامج المحاكاة الرياضي، لتقييم أداء تقنية تتبع نقطة القدرة العظمى، وأظهرت نتائج المحاكاة قدرة التقنية المعتمدة على تتبع نقطة القدرة العظمى بكفاءة، مما أدى إلى تحسين القدرة الكهربائية المستخرجة وزيادة كفاءة النظام واستقراره في ظل ظروف تشغيل مختلفة.

الكلمات المفتاحية:

تحويل الطاقة - النمذجة - تحسين الأنظمة - تتبع نقطة القدرة العظمى. (MPPT)

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Introduction générale

This dissertation is organized into four interconnected chapters, structured in a logical sequence to provide both the theoretical and practical aspects of photovoltaic (PV) systems and Maximum Power Point Tracking (MPPT) techniques, leading to the modeling, simulation, and performance evaluation of the proposed system. The organization of the dissertation follows a progressive approach, starting with the fundamental concepts before moving toward the implementation and analysis of the proposed solution.

Chapter One presents the theoretical background of photovoltaic energy. It introduces the fundamentals of solar radiation and explains the photovoltaic effect as the basic principle of electrical energy generation from sunlight. The chapter also discusses the structure and operating principle of photovoltaic cells and PV generators, their electrical characteristics, and the mathematical modeling of PV cells. Furthermore, it describes the different types of photovoltaic cells, analyzes the influence of environmental factors such as solar irradiance and temperature on PV performance, and highlights the main advantages and limitations of photovoltaic technology.

Chapter Two is devoted to DC-DC converters, which play a fundamental role in photovoltaic energy conversion systems. It introduces the basic concepts and operating principles of DC-DC converters, their main applications, and their importance in regulating and adapting the electrical power delivered by photovoltaic generators. The chapter also presents the most widely used converter topologies, namely Buck, Boost, and Buck-Boost converters, explaining their operating principles, characteristics, advantages, and applications. In addition, a comparative analysis of these converter topologies is provided in terms of voltage gain, efficiency, and operating performance.

Chapter Three focuses on Maximum Power Point Tracking (MPPT) techniques, which are essential for maximizing the energy extracted from photovoltaic systems under varying environmental conditions. It presents the operating principle of MPPT, its classification, and the most widely adopted tracking algorithms. Particular attention is given to the Perturb and Observe (P&O) and Incremental Conductance (INC) methods, as well as intelligent techniques such as Artificial Neural Networks (ANN) and Fuzzy Logic Control (FLC). The chapter discusses the operating principles, advantages, limitations, and practical applications of each technique, providing a comprehensive overview of their effectiveness in improving the efficiency of photovoltaic systems.

Finally, Chapter Four presents the modeling and simulation of the proposed photovoltaic system using MATLAB/Simulink. It describes the overall system architecture and the implementation of the selected MPPT technique, followed by the presentation and analysis of the simulation results. The performance of the proposed system is evaluated under different operating conditions, including variations in solar irradiance and temperature, in order to assess the tracking accuracy, dynamic response, stability, and overall efficiency of the MPPT strategy. The dissertation concludes with a general conclusion summarizing the main findings of this work and providing recommendations and future research perspectives for further improving the performance of photovoltaic energy conversion systems.

Etude bibliographique

Chapter 1: Literature of solar energy systems

1- Introduction:

Leveraging the Earth's most prolific energy asset, solar radiation serves as the fundamental input for photovoltaic (PV) technology. This system facilitates the direct conversion of solar irradiance into electrical power through specialized cells, exploiting the photovoltaic effect to harness renewable energy at its source.

Within this chapter, we will discuss the foundational principles of solar energy and describe the technical production of electricity via the photovoltaic effect.

Furthermore, we will explain how geographical and seasonal dynamics dictate the inherent variability of solar yield.

1.1. Overview and Motivation

The rapid growth in global electricity demand, largely driven by the continued reliance on fossil fuels such as oil and coal, has exerted significant pressure on finite fossil fuel reserves while simultaneously contributing to environmental degradation. The dependence on these conventional energy sources has resulted in substantial emissions of greenhouse gases, including nitrous oxide (N_2O), carbon dioxide (CO_2), and methane (CH_4), which are widely recognized as major drivers of climate change (IPCC, 2007).

In addition, the extensive use of fossil fuels in transportation systems and the continuous expansion of industrial activities have intensified air pollution levels, thereby exacerbating environmental and public health challenges [1, 2]. Maintaining economic development while preserving natural ecosystems for future generations requires a fundamental transition toward alternative, sustainable, and environmentally friendly energy resources. Achieving this transition demands coordinated international efforts and policy frameworks, as highlighted in global agreements such as the Kyoto Protocol [3].

Consequently, renewable energy sources (RES) have emerged as a promising and sustainable alternative for electricity generation. Over recent decades, the integration of renewable energy into power systems has expanded considerably, largely due to governmental policies and international initiatives aimed at reducing greenhouse gas emissions and promoting sustainable energy systems (World Energy Outlook). By 2023, renewable energy sources accounted for more than 33% of the global electricity generation capacity, as illustrated in Figure 1.1, reflecting their increasing role in the global energy portfolio [4]. Unlike fossil-based energy systems, renewable energy technologies including wind, solar, biomass, and hydro power generate electricity with minimal or no greenhouse gas emissions, thereby contributing significantly to climate change mitigation and improved air quality.

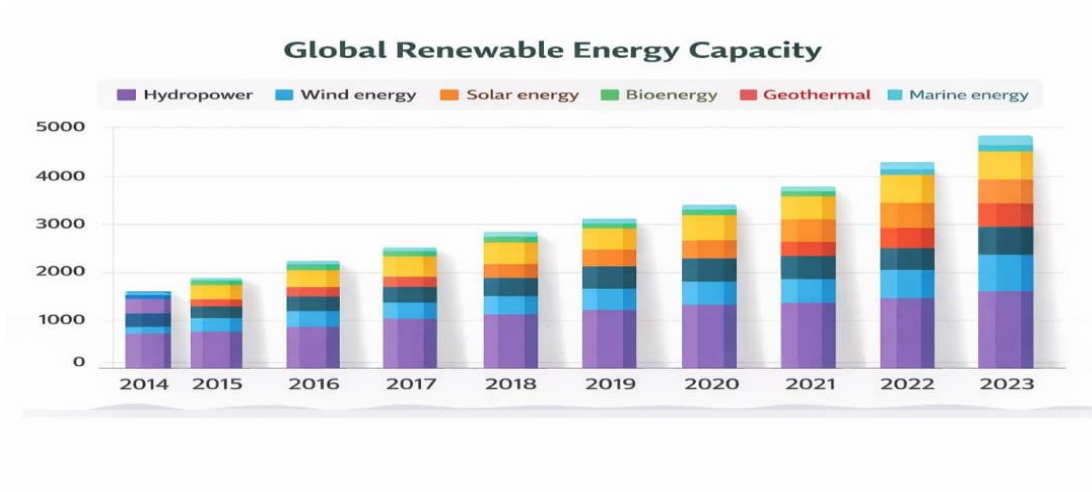


Figure 1: Global power generating capacity [4].

Among renewable energy technologies, solar photovoltaic (PV) and wind power have demonstrated the most significant expansion, surpassing other renewable energy sources in recent years. As indicated in Figure 1, PV systems and wind energy represent approximately 33% and 28% of newly installed renewable capacity, respectively. This rapid growth highlights their crucial role in the transition toward a low-carbon energy system. Furthermore, the potential for solar energy generation varies considerably across different geographical regions, as illustrated in Figure 1.3.

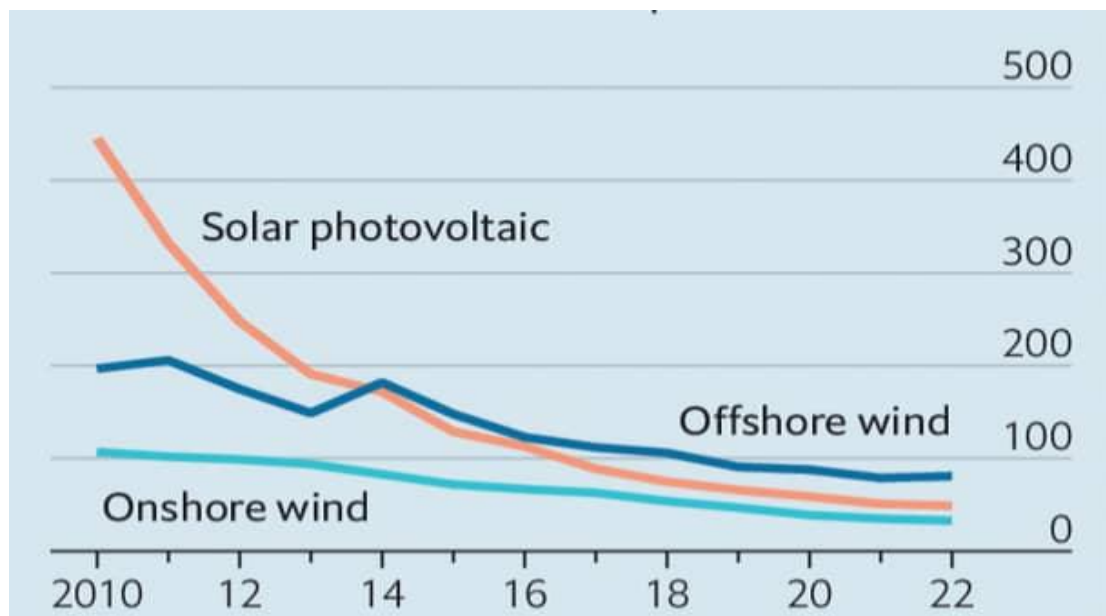


Figure 2: Levelised cost of electricity from newly commissioned solar PV, onshore wind power and offshore wind power, 2010-2022 [5].

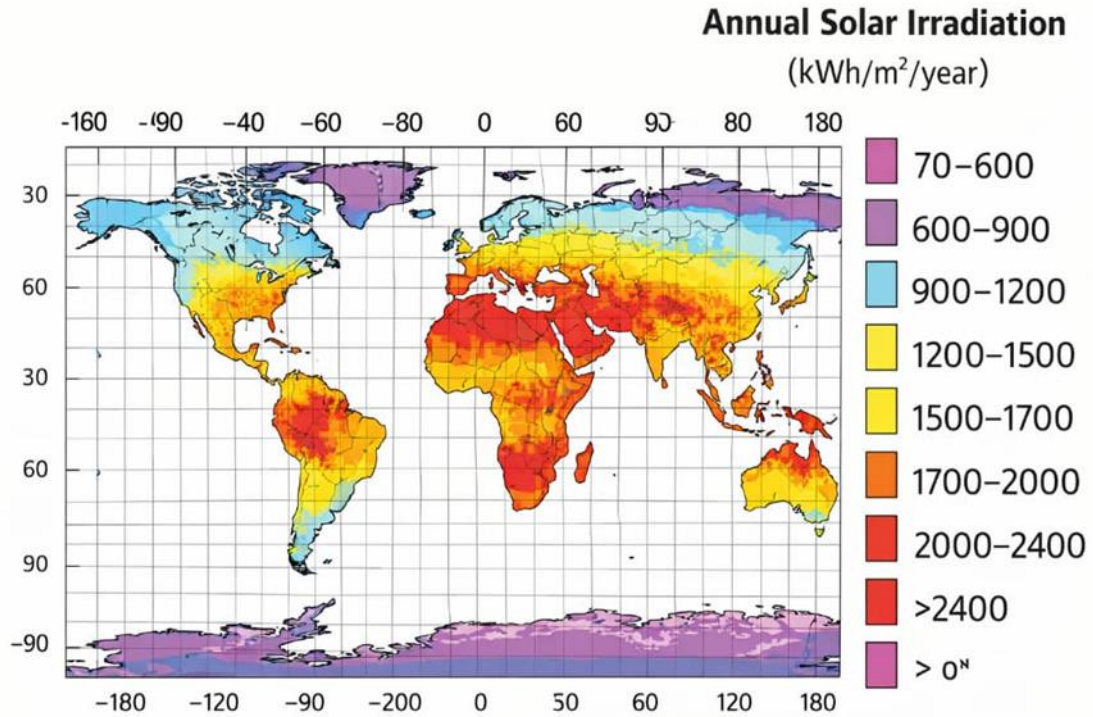


Figure 3: Solar irradiation map of the world from photovoltaic guidenr

The Levelized Cost of Electricity (LCOE) for renewable energy technologies has declined significantly over the past decade, reflecting continuous technological advancements and economies of scale. Among these technologies, onshore wind energy has experienced one of the most substantial cost reductions, with the global average LCOE decreasing by approximately 50% between 2010 and 2022 ,reaching nearly USD 0.033 per kilowatt-hour (kWh).

Similarly ,solar photovoltaic (PV) systems have undergone notable cost improvements, with the global average LCOE estimated at approximately USD 0.049 per kWh in 2022 .In comparison, offshore wind energy continues to exhibit relatively higher costs, with an LCOE of around USD 0.081 per kWh.

Despite these considerable improvements in economic viability, integrating renewable energy sources particularly solar PV into modern power systems remains technically challenging. This is primarily due to the intermittent and variable nature of renewable generation. Photovoltaic systems inherently produce direct current (DC) electricity whose voltage output fluctuates depending on environmental conditions such as solar irradiance and temperature. Consequently, direct integration of such systems into conventional electrical grids is impractical.

To address these challenges, power electronic converters (PECs) have emerged as essential components in renewable energy systems. These converters function as intermediary interfaces between renewable energy generators and the electrical grid. By regulating voltage and controlling power flow dynamically, PECs enable efficient power conversion, enhance grid stability, and ensure reliable integration and distribution of electricity generated from renewable sources.

1.2 Power Electronics Converters for Renewable Energy System

Power electronic converters (PECs) play a fundamental role in enabling the effective integration of renewable energy sources (RES) into modern electrical power systems. These converters act as essential interfaces between renewable energy generators and the electrical grid or load systems, ensuring compatibility between different voltage levels, current forms, and operating conditions. Consequently, their performance significantly influences the overall efficiency, reliability, stability, and power quality of renewable energy systems.

With the rapid growth of renewable energy technologies, the need for efficient and cost-effective energy conversion solutions has become increasingly important. In this context, advanced converter technologies and innovative energy conversion systems, including photo-electrochemical (PEC) technologies, are being actively investigated to enhance system performance and energy utilization [4]. Figure 1.4 illustrates a general framework describing how renewable energy sources can be integrated into electrical power systems through the application of power electronic converters.

The successful integration of renewable energy sources into power networks requires the use of appropriate power electronic interfaces capable of regulating and conditioning the electrical output of these sources to meet grid requirements. As a result, considerable research efforts have been dedicated to improving converter efficiency and operational flexibility. These improvements are generally achieved through two primary approaches: the development of advanced converter topologies and the implementation of sophisticated control strategies that optimize system performance.

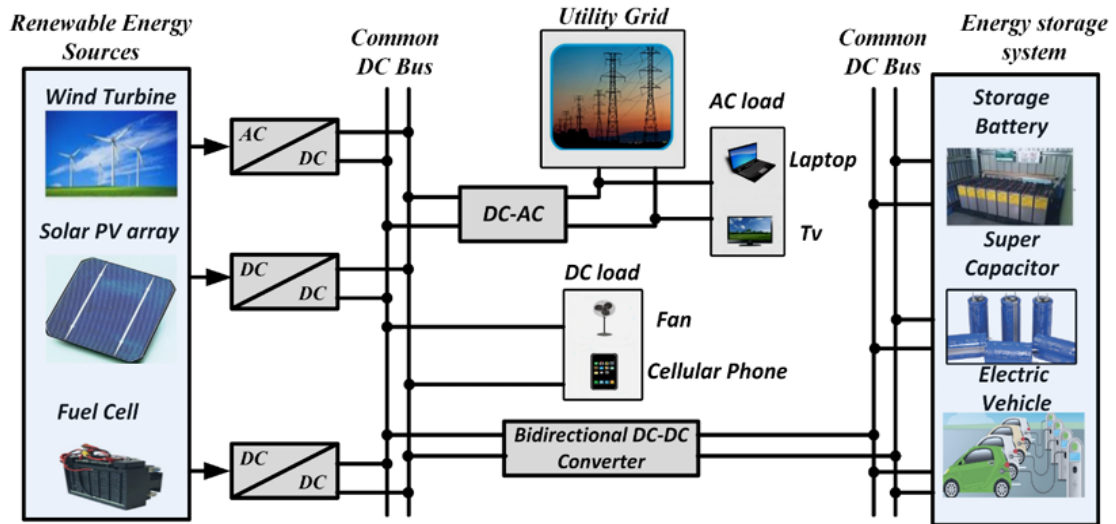


Figure 4: Schematic exhibiting the relationship of a RES to the electricity grid.

Power electronic converters used in renewable energy systems (RES) can generally be classified into two main categories: galvanically isolated converters and non-isolated converters [6], [7]. Galvanically isolated converters, also referred to as transformer-based converters, employ a transformer to provide electrical isolation between the input and output terminals. This isolation improves operational safety and offers greater flexibility in the design of power conversion systems, as highlighted in several studies addressing the topological analysis of these converters [8]–[10].

Despite the advantages provided by galvanic isolation, the incorporation of transformers introduces several technical and economic challenges. The presence of a transformer increases the overall system cost and physical size, and may also reduce operational efficiency due to additional conversion losses. In contrast, non-isolated converters, often known as transformerless converters, feature simpler structures, higher efficiency, and relatively lower cost. These advantages have been confirmed by numerous experimental studies and practical implementations [11], [12].

Therefore, non-isolated converters have become a more favorable option in many renewable energy power conversion applications, particularly when system efficiency, compact design, and cost reduction are considered essential design criteria while maintaining reliable system performance.

1.2.1 Review of PV Energy System Applications

Photovoltaic (PV) energy systems represent one of the most widely adopted technologies for integrating renewable energy into modern electrical power networks. These systems provide a sustainable and environmentally friendly approach to electricity generation by converting

solar irradiance directly into electrical energy. Typically, a PV energy conversion system begins with photovoltaic arrays that capture solar radiation and generate direct current (DC) power.

The generated DC power is commonly regulated and stabilized through a DC-link or DC bus structure to ensure consistent system operation. A power electronic converter, often implemented using multilevel inverter technology, plays a critical role in transforming the DC power into alternating current (AC) suitable for grid-connected applications. This conversion process is designed to produce high-quality output power while minimizing total harmonic distortion (THD), thereby satisfying grid power quality requirements.

In addition, filtering components are employed to mitigate high-frequency switching harmonics and electromagnetic interference, ensuring compliance with grid standards and improving overall system performance. In some configurations, a transformer may be included to provide voltage level adjustment and galvanic isolation between the photovoltaic system and the utility grid, enhancing operational safety and system protection.

Furthermore, the system is governed by an advanced control unit that integrates a Maximum Power Point Tracking (MPPT) algorithm. The MPPT controller continuously monitors the operating conditions of the PV array and adjusts the converter operation to extract the maximum available power under varying environmental conditions such as solar irradiance and temperature. Finally, the converted AC power is delivered to the utility grid, illustrating the coordinated operation of power electronic converters, control algorithms, and energy conversion technologies for efficient solar energy utilization and reliable grid integration.

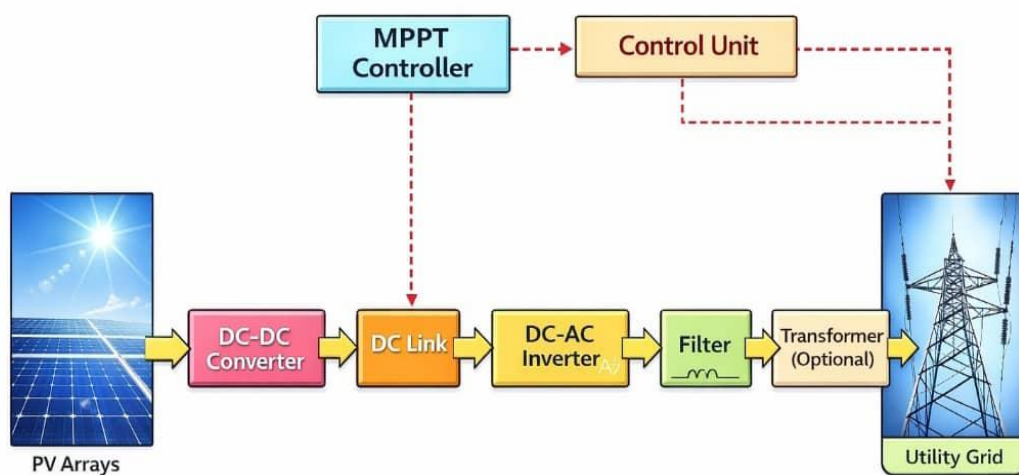


Figure 5: A photovoltaic (PV) system with power electronics and the needed control.

1.2.2 Classification of power converters

Power electronic converters are widely employed in industrial applications to ensure efficient energy conversion and optimal power management. According to the type of electrical energy conversion and the direction of power flow, these converters are generally classified into four main categories:

- AC–DC rectifiers: Devices that convert single-phase or three-phase AC voltage into DC voltage, commonly used as front-end stages in variable-speed motor drives and renewable energy systems.
- DC–DC converters: Circuits that transform a DC voltage level into another DC level, and in some applications may also change the polarity.
- DC–AC inverters: Systems that convert DC power into AC power with controllable voltage and frequency, widely used in motor drives and grid-connected renewable energy systems.
- AC–AC converters (cyclo converters): Converters that transform an AC voltage into another AC voltage with different amplitude, frequency, or number of phases.

1.2.3 Classification of DC–DC converters

DC–DC converters are the cornerstone of renewable energy and storage systems, with research focusing on enhancing their efficiency and minimizing losses. These converters are technically classified according to their switching mechanism into three main modes in Figure [13–15]: Linear Mode converters, which are characterized by design simplicity, fast response, and low noise, but suffer from low efficiency due to power dissipation; Hard Switching Mode converters, which include topologies such as "Buck," "Boost," and "Cuk," typically used in non-isolated "chopper" applications, with the necessity of using galvanic isolation when connected to the power grid to ensure safety; and Soft Switching Mode converters, which were developed to reduce switching stresses and losses. The importance of these converters is highlighted in voltage regulation within microgrids to feed diverse loads, where constant power loads (CPLs) pose a significant technical challenge due to their non-linear characteristics that destabilize the system voltage, necessitating the use of advanced control strategies that transcend traditional techniques [16, 17].

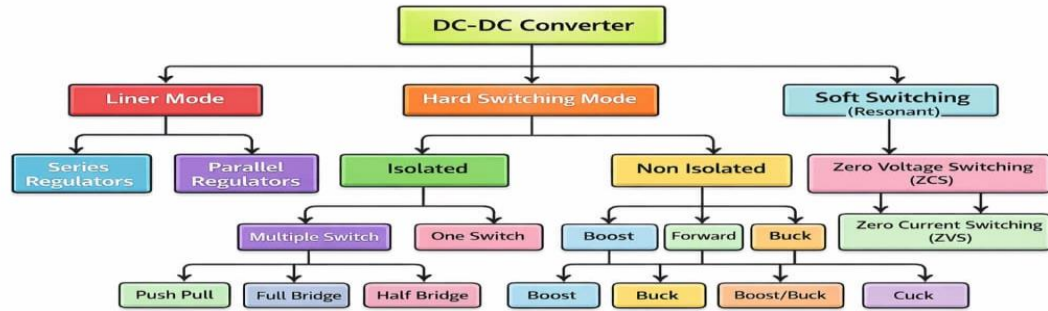


Figure 6: Classification of DC–DC converters [18].

2- Solar Radiation:

Solar radiation comprises the total electromagnetic emission from the Sun, ranging from high-energy cosmic particles to the broad wave spectrum. Thermodynamically, this emission is accurately modeled as a black body at a temperature of 5800 k, as dictated by Planck's law.

The spectral irradiance reaches its peak in the yellow spectrum at $\lambda=570$ nm, with energy distribution nearly balanced between visible light and infrared, while ultraviolet radiation accounts for approximately 1%.

Upon atmospheric entry, this radiation undergoes complex 'filtering' through selective absorption bands most notably by ozone, oxygen, carbon dioxide, and water vapor which reconfigures the spectral power distribution before it reaches sea level [1].

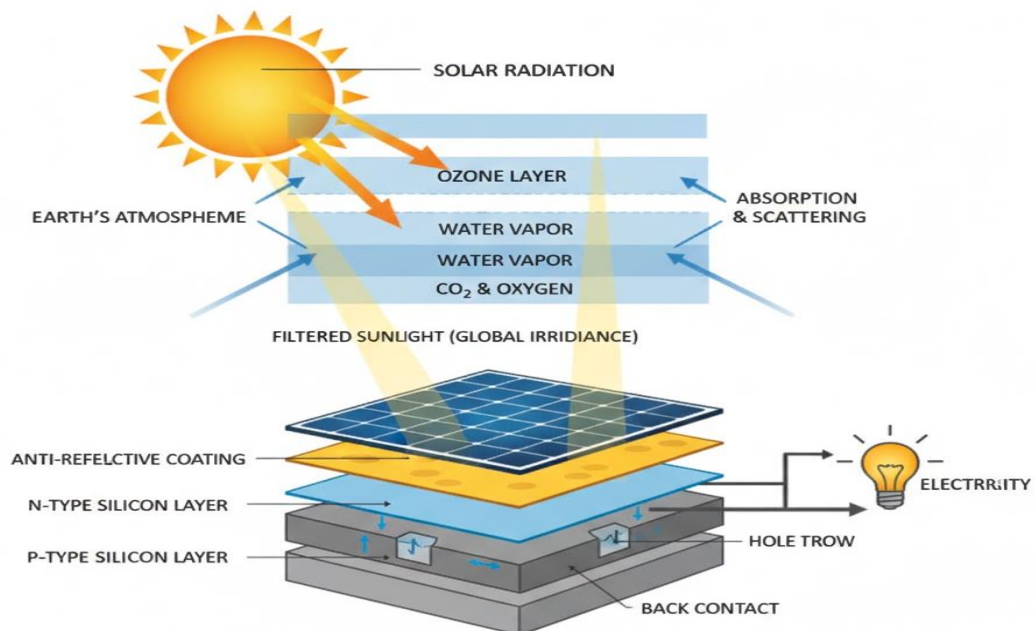


Figure 7: Representation of Solar Radiation

3- Radiation Spectrum:

Solar energy, traditionally perceived as solar irradiance and thermal flux, has been redefined by the advent of photovoltaic technology.

This innovation facilitates the quantum transition of solar photons into a continuous electrical current, bridging the gap between natural electromagnetic radiation and the escalating energy demands of modern infrastructure.

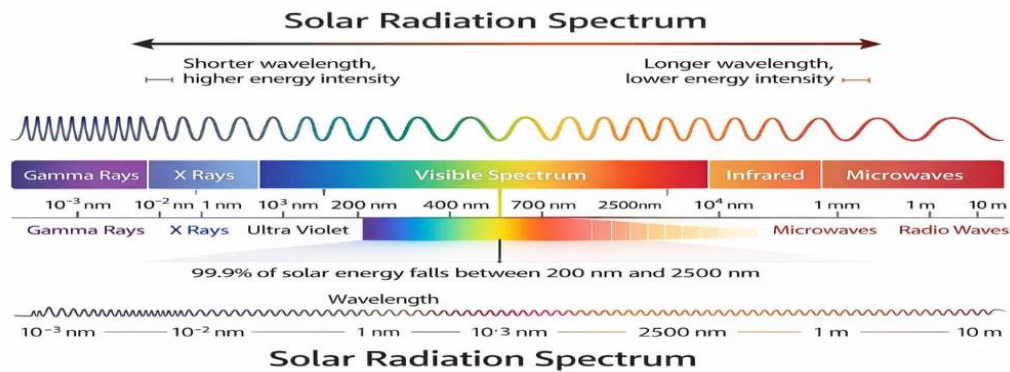


Figure 8: Representation of Solar Radiation

While the electromagnetic spectrum is vast, **99.8%** of solar radiant energy is concentrated within a narrow band of **20–2500 nm**.

Atmospheric and ionospheric interactions ensure that only a small fraction reaches Earth ranging from decameter radio waves to soft UV rays while the rest is reflected or absorbed [2].

As depicted in **Figure 8**, this solar flux comprises **5%** ultraviolet, **42%** visible, and **53%** near-infrared radiation.

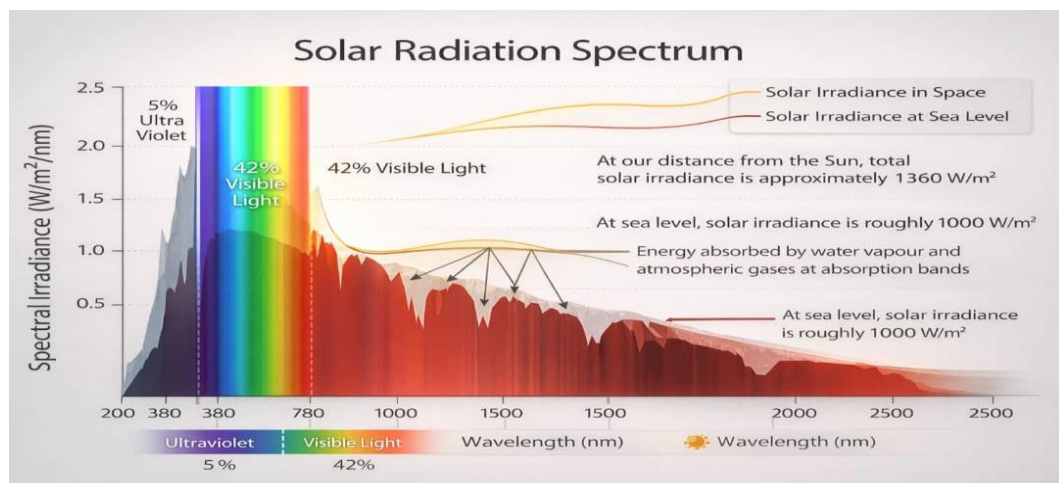


Figure 9: Representation of Solar Radiation Spectrum

4- Conversion of Solar Radiation by PV Effect:

A PV cell is structured as a semiconductor P-N junction composed of two distinctively doped silicon layers.

The P to type layer is synthesized through boron incorporation, while the N-type layer is doped with phosphorus, establishing an electrostatic potential barrier at the interface.

Upon the absorption of photons with energy exceeding the material's band gap, valence bonds are disrupted, facilitating the generation of electron to hole pairs.

This phenomenon, known as the photovoltaic effect, manifests as a potential difference across the junction.

Once an external circuit is established, the biased migration of charge carriers induces a steady electric current [1].

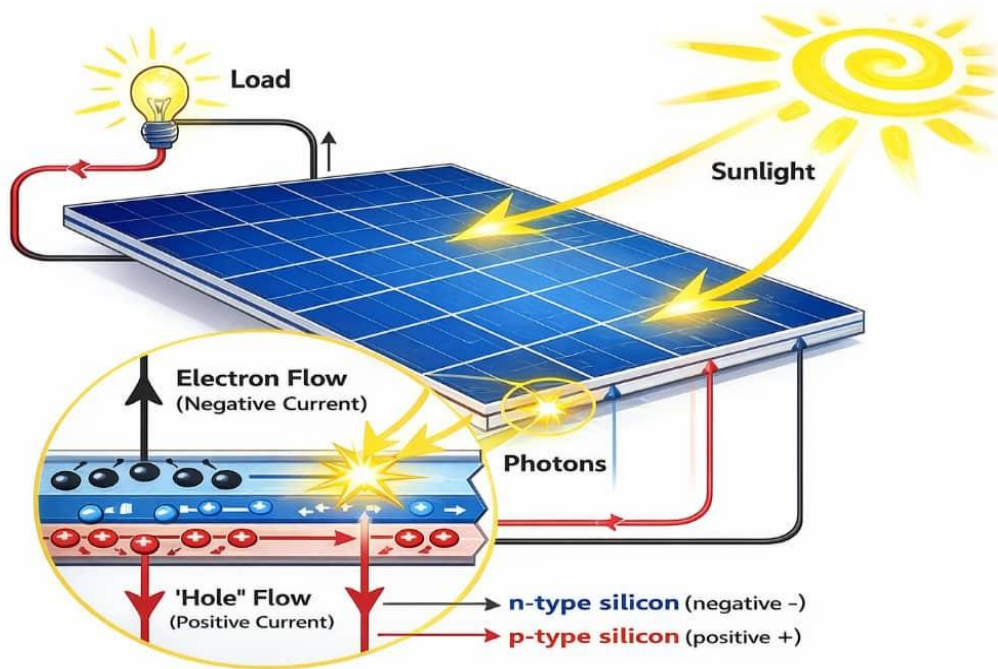


Figure 10: Solar Radiation Conversion by PV Effect

5- Photovoltaic Generator:

The photovoltaic sensor is characterized by its electrical properties, particularly the relationship between current and voltage ($I=f(V)$), as illustrated in Figure 10.

This modelling is commonly used to estimate the sensor output (voltage, current) based on two input variables: temperature and the illumination received by the sensor.

The current produced by the photovoltaic module at a given voltage depends exclusively on the illumination and the temperature of the cell. With temperature and illumination constant,

the efficiency of a solar cell is influenced by the load present in the electrical circuit. In an open circuit configuration ($R_c = \infty$, $I = 0$, $V = V_{oc}$) or a short circuit ($R_c = 0$, $I = I_{sc}$, $V = 0$), no energy is transmitted outside. Between these two extremes, an optimal value R_{opt} of the load resistance R_c exists, for which the power.

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

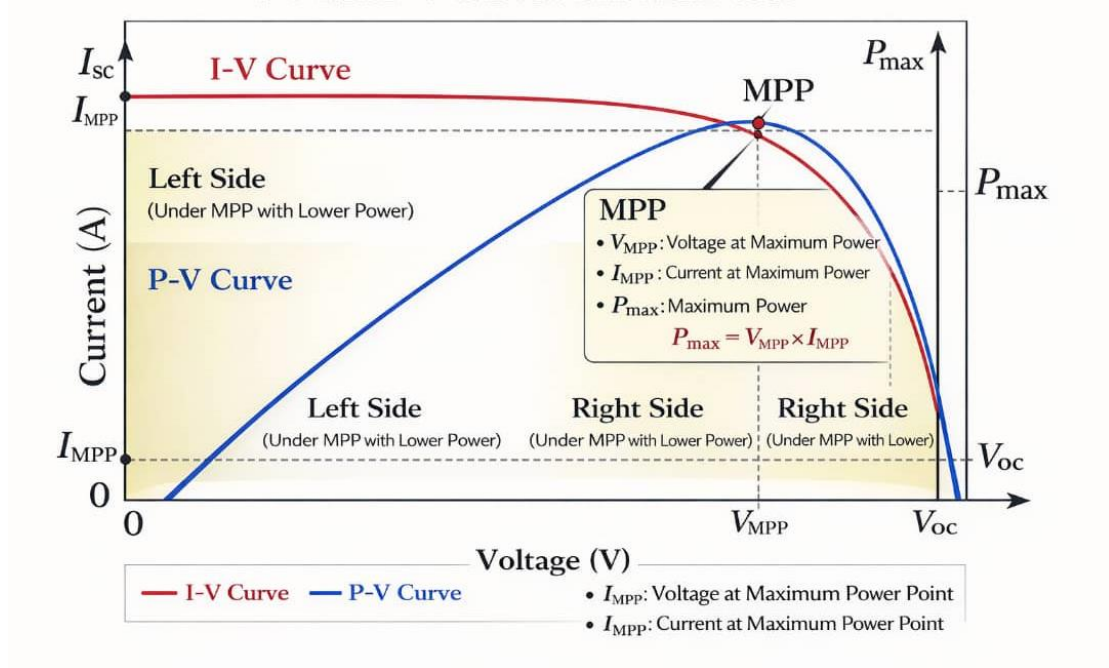


Figure 11: Typical Characteristics of a PV Generator

The energy efficiency of the solar cell is defined as $\eta = P/P\gamma$, where $P\gamma$ is the incident light power on the surface of the cell. For the optimal value R_{opt} of the load resistance R_c , the efficiency of the solar cell is maximum, and $\eta_{max} = P_{max}/P\gamma$. The value of R_{opt} is not a characteristic constant for a given cell, but depends on the spectrum of the incident radiation and the junction temperature. In fact, the efficiency decreases as the temperature increases, which sometimes leads to the construction of hybrid sensors resulting from the combination of a thermal sensor and a solar cell. These sensors allow the simultaneous production of hot water and increase the photovoltaic efficiency by cooling the cell.

The power provided by the solar cell ($P = I \times V$) and its efficiency depend on the material used and the manufacturing technology (amorphous silicon, polycrystalline silicon, monocrystalline silicon), the junction geometry (layer thickness, multilayers, etc.), and external parameters (temperature, spectrum and power of the incident radiation, external electrical circuit connected to the cell, etc.).



Figure 12: Block Diagram of a PV Generator

5-1- Photovoltaic Cell:

Photovoltaic modules consist of an arrangement of interconnected solar cells. These cells are embedded in resin and encapsulated between two tempered glass panes (double-glass modules) or between a glass pane and a Tedlar sheet (glass/Tedlar module). Typically, this assembly is inserted into an anodized aluminium frame, although frameless modules are available for building integration applications, using aluminium profiles on facades or roofs. The power that a module can provide depends on its surface area and the incident solar irradiation, expressed in peak watts (W_p), and represents the maximum power of the module for a reference maximum solar irradiation (1000 W/m^2).

The voltage delivered by a module depends on the number of cells connected in series. For low-power modules ($< 75 \text{ W}_p$), the operating voltage is generally between 12 and 15 volts. Higher power modules are obtained by increasing the number of cells in series, which results in an "increase in voltage," and by increasing the number of cell branches in parallel, which causes an "increase in current value." The operating voltage can then be 24 volts or more, depending on the system configuration to be powered. The surface area of the modules varies among manufacturers, typically between 0.5 and 1 square meter; it can reach 3 square meters for special productions and large orders. Several interconnected modules form a panel, and several interconnected panels make up a photovoltaic array. Assembling modules in series and/or in parallel allows generating different voltages and powers [1].

5-2- Modelling of a PV Cell:

The operational behavior of a PV module is fundamentally governed by the Shockley single-diode model, scaled from a single cell to a modular array via series-parallel configurations.

Electrically, the cell is modeled as a current source shunted by a diode, with two critical resistive components accounting for physical losses:

- **Series Resistance (R_s):** Represents ohmic losses arising from semiconductor bulk resistance, grid contact resistance, and busbar resistivity.
- **Shunt Resistance (R_p):** Accounts for junction leakage currents resulting from fabrication imperfections.

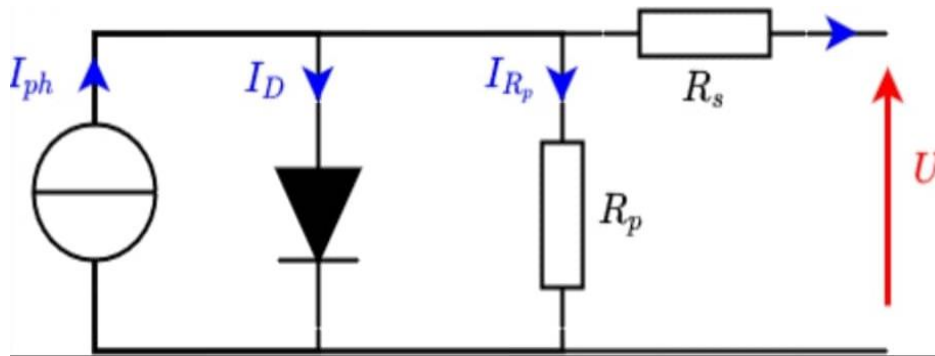


Figure 13: Equivalent Circuit of a PV Cell

6- Types of Photovoltaic Cells :

Photovoltaic solar panels are made up of photovoltaic cells and vary according to type:

6-1-Monocrystalline Cells:

Monocrystalline silicon results from the cooling of molten silicon. Once solidified, it transforms into a uniform crystal that is cut into thin slices to form the photovoltaic cell. The colour of this material is blue, without any trace of crystals or other impurities.

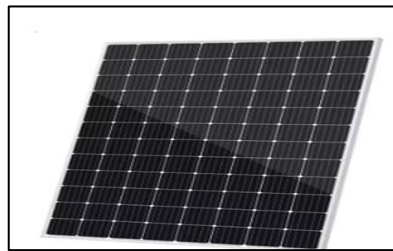


Figure 14: Monocrystalline Cells

6-2- Polycrystalline Cells:

Polycrystalline silicon is obtained by melting silicon in a square and elongated metal mold, called an ingot. The color of this type of cell is blue and speckled with patterns left by the crystals. This characteristic allows us to easily recognize this photovoltaic cell.



Figure 15: Polycrystalline Cells

6-3- Hydrogenated Amorphous Cells:

Amorphous silicon is obtained from silicon gas. This gas is vaporized onto a support, either glass, flexible plastic, or metal, using a vacuum deposition process. These PV cells are dark gray.



Figure 16: Hydrogenated Amorphous Cells

7- The Impact of Temperature on Solar Panel:

Temperature has a significant impact on the performance of solar panels. Here's how:

- **Reduction in Efficiency:** As the temperature of solar panels increases, their efficiency decreases. Solar panels work by converting sunlight into electricity, and as the temperature rises, the efficiency of this conversion decreases.
- **Voltage Decrease:** The voltage of a solar panel decreases as its temperature increases. This is due to the fact that the semiconductor material in solar panels becomes less efficient at transporting charges as temperature increases.
- **Power Output Reduction:** Higher temperatures can lead to a decrease in the power output of solar panels. This is because the decrease in efficiency and voltage negatively impacts the overall power output.

- **Thermal Degradation:** High temperatures can cause thermal degradation of solar panel materials over time, reducing their lifespan and efficiency.
- **Operating Temperature Range:** Solar panels are designed to operate within a certain temperature range. If temperatures exceed this range, the performance of the panels can be further compromised.

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

8- Advantages and Disadvantages of PV Energy:

8-1- Advantages:

- **Renewable Energy Source:** Solar energy is an inexhaustible and globally abundant resource that can be harnessed sustainably without depleting natural reserves.
- **Decarbonization & Low Emissions:** Solar power generation produces zero greenhouse gas emissions, significantly reducing carbon footprints and supporting global climate mitigation efforts.
- **Decreasing Cost Trajectory:** Ongoing technological advancements have led to a substantial reduction in PV system costs, making solar energy increasingly competitive with conventional fossil fuels.
- **Energy Independence:** Photovoltaic systems empower consumers to generate decentralized electricity, mitigating reliance on external utility providers and insulating them from market price volatility.
- **Minimal Maintenance Requirements:** Once installed, solar arrays require negligible upkeep, resulting in lower long-term operational and maintenance (O&M) expenditures.

8-2- Disadvantages:

- **Intermittency & Variability:** Power output is strictly dependent on solar availability, leading to fluctuations that necessitate energy storage solutions or integration with auxiliary power sources.
- **Substantial Initial Investment:** Despite declining prices, the upfront capital expenditure (CAPEX) for solar installation remains relatively high.
- **Lifecycle Environmental Impact:** While clean during operation, the manufacturing and decommissioning phases of solar panels involve chemical processes that may pose environmental challenges.
- **Spatial Requirements:** Large-scale solar deployment demands significant land or rooftop surface area, which can be a constraint in high-density urban environments.

- **Climatic Dependency:** Adverse meteorological conditions, such as cloud cover, rain, or snow, can degrade system performance and reduce overall energy conversion efficiency.

9- Conclusion:

In conclusion, this chapter has established a comprehensive foundation regarding solar irradiance and photovoltaic energy conversion. It has elucidated the mechanisms through which solar cells leverage the photovoltaic effect to generate electricity from sunlight. Furthermore, the modeling of PV generator characteristics was analyzed, emphasizing critical efficiency determinants such as operating temperature and load impedance.

The chapter also categorized various photovoltaic cell technologies based on silicon crystalline structures and detailed the structural components of PV modules. Finally, a critical assessment of the primary advantages and inherent limitations of solar technology was presented, providing a balanced perspective on its current role in the energy landscape.

Chapter 2

DC-DC Converter

1- Introduction:

DC-DC converters play a fundamental role in photovoltaic (PV) energy conversion systems by ensuring efficient voltage regulation and optimal power transfer between the PV generator and the load. Since the output voltage of photovoltaic modules varies continuously with changes in solar irradiance, temperature, and load conditions, an intermediate power conversion stage is required to provide a stable and controllable output. In addition, DC-DC converters enable the implementation of Maximum Power Point Tracking (MPPT) techniques, allowing photovoltaic systems to operate at their maximum power point and thereby improving their overall efficiency.

Several converter topologies have been developed to satisfy different voltage conversion requirements. Among the most widely used are the Buck, Boost, and Buck-Boost converters, each characterized by a specific operating principle and voltage conversion capability. The appropriate selection of a converter topology is essential for achieving high conversion efficiency, reliable operation, and effective integration with photovoltaic systems.

This chapter presents the fundamental concepts of DC-DC converters, their operating principles, and their major applications in photovoltaic systems. It also discusses the Buck, Boost, and Buck-Boost converter topologies, highlighting their operating modes, characteristics, and performance. Finally, a comparative analysis of these converters is presented, providing the theoretical background necessary for the study of MPPT techniques discussed in the next chapter..

2- DC-DC Converters :

DC-DC converters are static power converters that transform a DC source into a precisely adjustable output for various loads. Structurally, they utilize thyristors for high-power applications (up to several 100 MW) at low chopping frequencies. Alternatively, for lower power demands up to 100 kW transistors are preferred, enabling high-frequency switching up to 100 kHz to optimize efficiency and system size.

The following figure represents the standardized symbol for these converters.

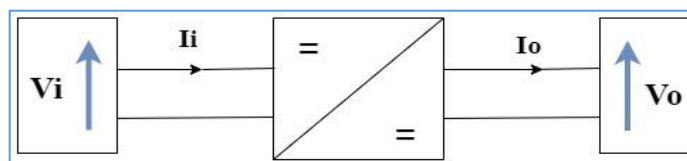


Figure 17: DC-DC Converters

3- Applications of DC-DC Converter:

Over the past few years, switch-mode power converters have established themselves as a cornerstone of contemporary electronics, penetrating diverse sectors ranging from industrial and utility to consumer markets.

In the realm of low-power applications, while the majority of requirements are met by conventional Buck, Boost, and Buck-Boost topologies, specialized high-demand scenarios necessitate more advanced and modified configurations.

It is essential to recognize that there is no 'one-size-fits-all' solution in the literature; rather, conversion techniques are precisely tailored to their specific environments. These converters are pivotal in the field of Power Electronics and Energy Drives, with their impact being most profound in high-voltage gain applications.

This includes sophisticated systems such as radar technology, data centers, and the strategic harnessing of renewable energy.

In fact, the role of high-gain DC-DC converters is particularly critical in renewable energy integration, where they facilitate the essential voltage boosting required for grid synchronization.

Furthermore, the shift towards DC distribution systems offers a multitude of systemic advantages including a reduction in conversion stages, cost-efficiency, and superior power quality positioning these converters as the preferred choice for the next generation of power infrastructure.



Figure 18: Applications of DC/DC Converters.

Here are some of DC-DC converter applications:

- **Renewable Energy Integration:** In the frontier of renewable energy, DC-DC converters are engineered to draw continuous, low-ripple input currents to ensure source stability. High-voltage gain, non-isolated interleaved topologies are the preferred architecture for interfacing renewables with microgrids, providing the necessary voltage boost while maintaining high efficiency and seamless integration across diverse energy sources.
- **Medical Instrumentation & Safety:** For medical applications, galvanic isolation is a non-negotiable safety imperative, serving to decouple sensitive patient-end outputs from hazardous input-side potentials. However, in specific high-energy medical systems like X-ray power supplies, non-isolated configurations are strategically deployed to meet rigorous power delivery requirements without compromising performance.
- **Automotive Electrification (EV/HEV):** In the automotive sector, the DC-DC converter acts as the central power arbitrator, stepping down energy from the high-voltage traction battery to stabilized low-voltage domains for auxiliary systems like lighting and cabin controls. Buck-boost topologies provide the necessary bidirectional flexibility, while charge-pump converters are utilized for precise voltage inversion, ensuring complete separation between high-voltage propulsion and low-voltage control logic.
- **Smart Illumination Architectures:** Modern LED-based smart lighting demands sophisticated driver solutions characterized by PWM-based precision control and high luminous efficiency. By employing a spectrum of technologies ranging from linear regulators to advanced switching converters these drivers ensure robust voltage protection and constant current regulation, achieving a synergy between simple design and high-performance output.

4- Types of DC-DC converters:

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

4-1- Buck Converter:

Functional and Dynamic Analysis The Buck Converter stands as a sophisticated Switch-Mode Power Supply (SMPS) topology, fundamentally engineered to perform efficient step-down DC-to-DC conversion.

Unlike dissipative linear regulators, its operating principle hinges on Pulse Width Modulation (PWM) to regulate the average output voltage by orchestrating the high-frequency switching of a semiconductor device.

During the On-state, the inductor functions as an electromagnetic energy reservoir, accumulating energy as the current ramps linearly.

Conversely, during the Off-state, the inductor reverses its polarity to maintain current continuity through a freewheeling diode, effectively acting as a temporary source for the load.

By integrating this switching action with a second-order LC low-pass filter, the converter attenuates high-frequency harmonics to extract a stable DC component.

The output magnitude is governed by the ideal steady-state transfer function $V_{out} = D \cdot V_{in}$, where the Duty Cycle D serves as the primary control variable for dynamic voltage regulation.

Operating Principle of Buck Converter

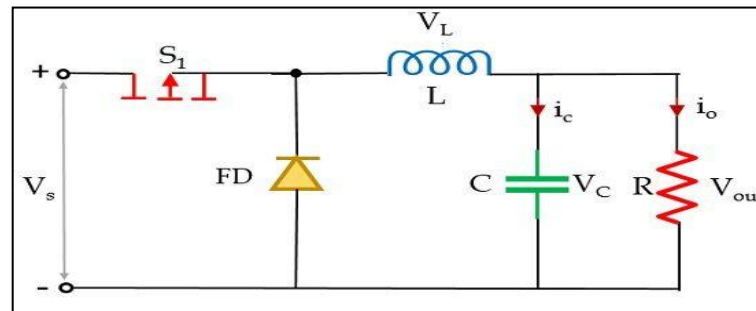


Figure 19: The Circuit Representation of Buck Converter

The engineering design of the Buck Converter is centered on the seamless integration of the Switching Network and the Filtering Network to ensure high-efficiency power transduction:

1. **Dual-Switching Topology:** The circuit incorporates two active elements for power flow control: the solid-state power MOSFET, serving as the primary control switch, and the Freewheeling Diode. This switching combination ensures the continuity of the inductive current path and prevents destructive voltage spikes (transients) that could occur during switching intervals.
2. **Second-Order LC Filter:** The switching network is coupled with a low-pass filter consisting of an Inductor (L) and a Capacitor (C). This network is designed to attenuate high-frequency harmonics generated by the switching process, thereby minimizing voltage and current ripples to their lowest theoretical limits. This results in a stable, regulated DC output across a pure resistive load.

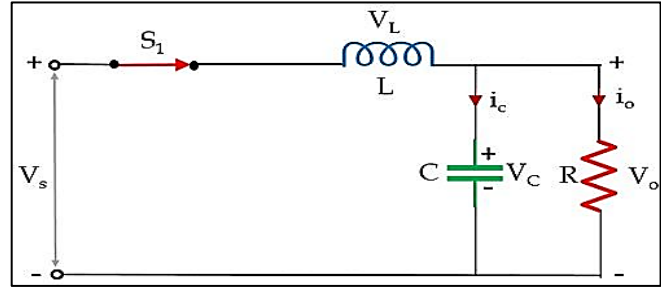


Figure 20: Buck Converter When S_1 is Closed

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 S_1 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 S_1 is closed.

Now, the second mode of operation takes place when switch S_2 is closed and S_1 gets open. However, you must be thinking about how automatically, the switch S_2 will be closed. So, as we have discussed that the inductor in the circuit will store the energy so, once S_1 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:

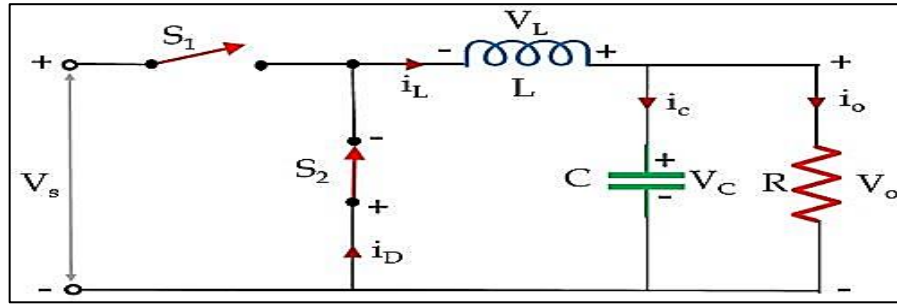


Figure 21: Buck Converter When S_2 is Closed

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,

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

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

On simplifying,

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

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

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

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

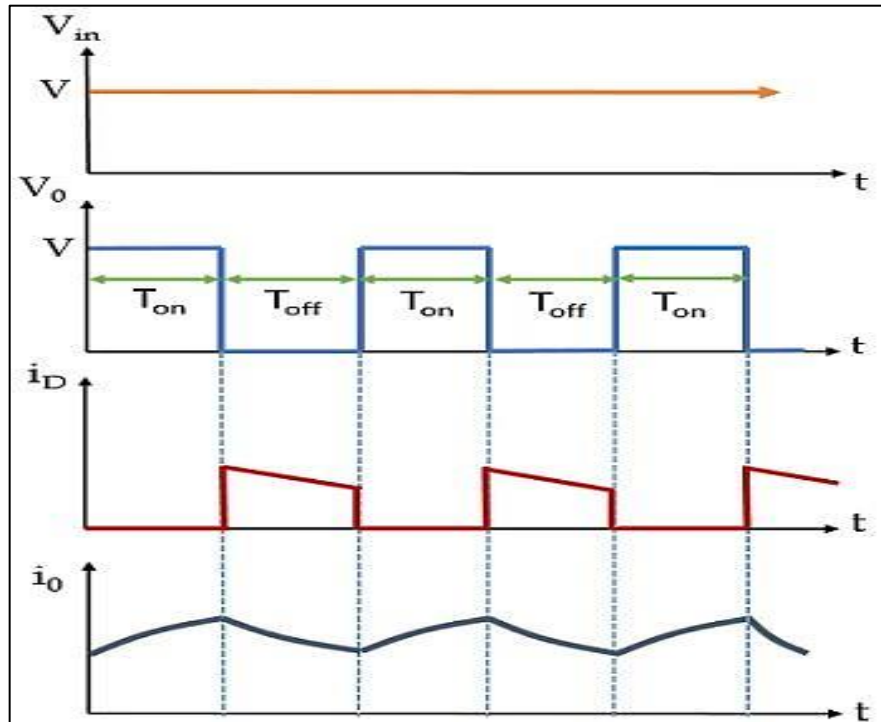


Figure 22: Waveform Representation

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

4-2- Boost Converter :

Boost Converters, fundamentally recognized as step-up DC-DC converters, represent a class of switching-mode topologies engineered to deliver an output potential exceeding the primary source voltage.

Within these architectures, the energy transduction mechanism ensures that the synthesized DC output possesses a higher magnitude relative to the supply input.

The nomenclature 'Boost' is analytically derived from the circuit's inherent capability to elevate the steady-state voltage levels throughout the conversion process.

Operating Principle of Boost Converter

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

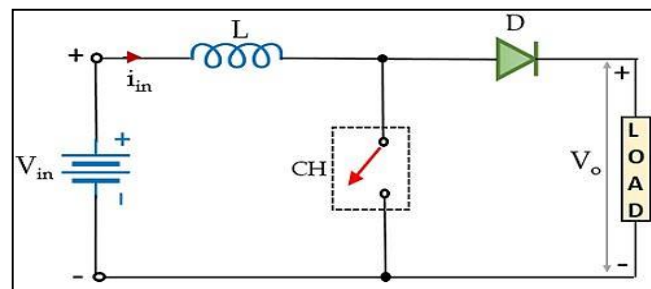


Figure 23: Elementary Circuit of Boost Converter

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.

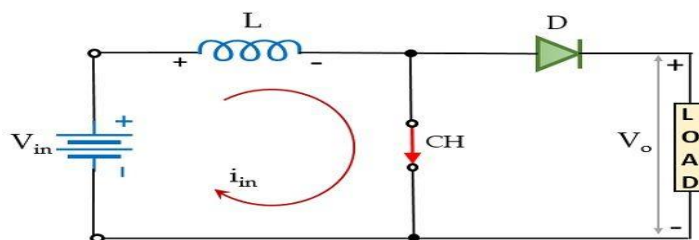
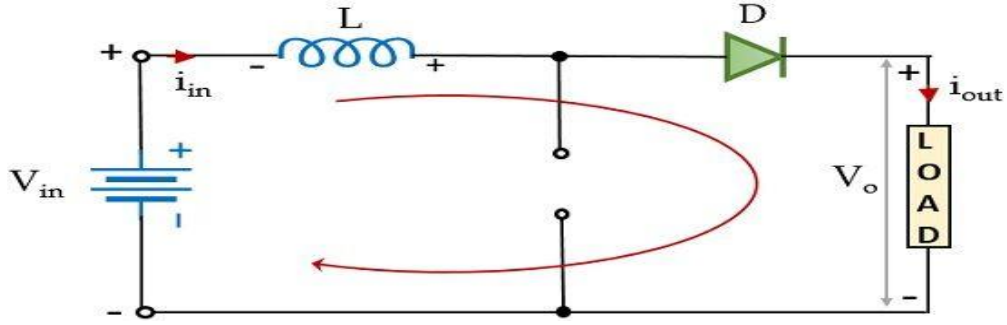


Figure 24: The Chopper CH is in on State

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 25: 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:

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

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:

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

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

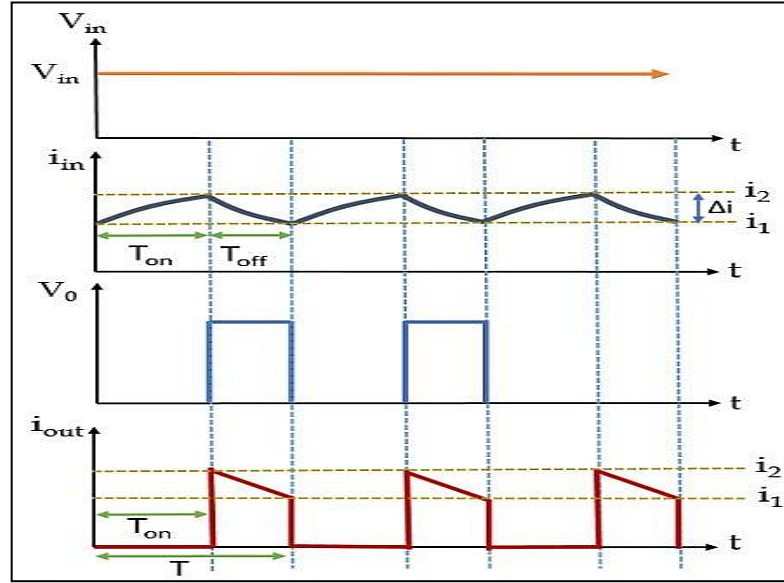


Figure 26: Waveform Representation

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,

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

This means,

$$V = V_{oL} - V_{in}$$

$$V = V_{oL} - V_{in} \quad (II. 28)$$

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.

4-3- Buck-Boost Converter:

The Buck–Boost converter represents a specialized class of DC-to-DC converters capable of generating an output voltage magnitude that is either superior or inferior to the input potential.

Functioning as a DC equivalent to an AC transformer, it facilitates precise voltage scaling and is topologically analogous to a single-inductor fly-back converter.

Within the hierarchy of switching-mode regulators, commonly designated as choppers, the Buck-Boost variant is distinguished by its operational versatility.

This converter can dynamically transition between step-down and step-up modes, a function dictated strictly by the modulation of its duty cycle (D).

A standard representation of this architecture is illustrated in the schematic below:

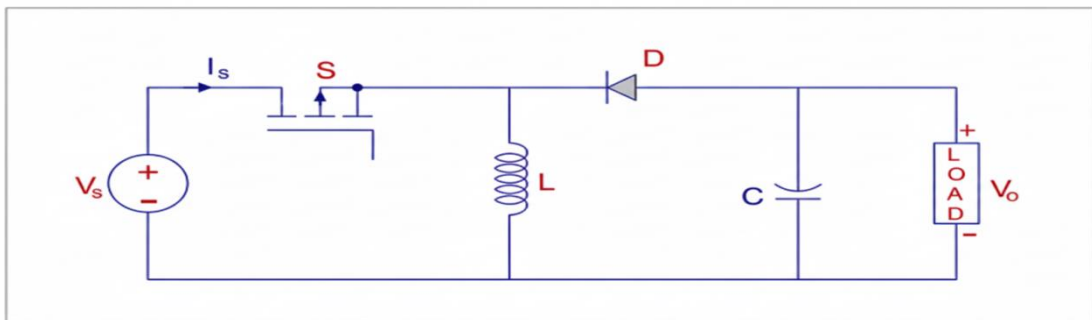


Figure 27: The Circuit Representation of Buck-Boost Converter

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.

Mode I: Switch is ON, Diode is OFF

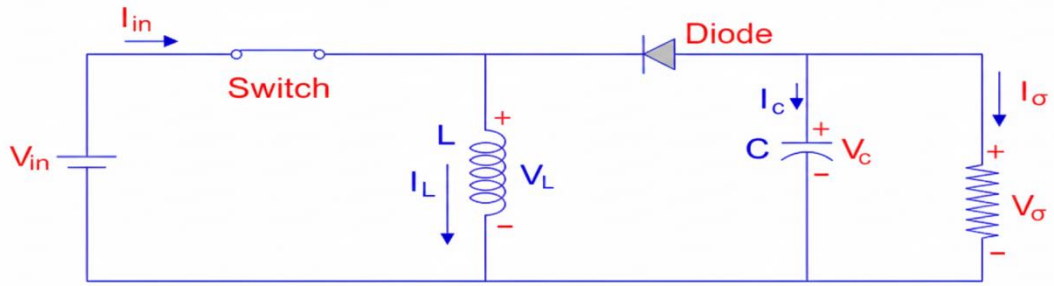


Figure 28: The Equivalent Circuit of Mode I

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:

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

and the switching frequency:

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

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.

Mode II: Switch is OFF, Diode is ON

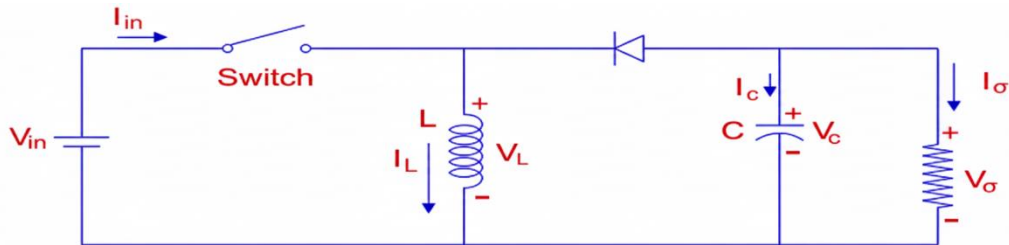


Figure 29: The Equivalent Circuit of Mode II

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.

4-4- 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.

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

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

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

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].

5- Comparison of Converter Types :

Table (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].

Table 1: Comparison of Converter Types.

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

6- Efficiency of Static Converters :

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

Table 2: Efficiency of Static Converters.

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

7- Conclusion :

In summary, DC-DC converters constitute the backbone of contemporary power electronics, ensuring high-efficiency energy regulation through precise voltage transformation.

The diverse topologies comprising Buck, Boost, and Buck-Boost configurations provide the necessary flexibility to satisfy the complex electrical demands of modern electronic architectures.

These switching regulators are pivotal across multiple sectors, including automotive engineering, telecommunications, and renewable energy infrastructure. Their utility scales from low-power consumer gadgets to high-capacity energy management in large-scale photovoltaic arrays, making them essential for modern power flow control.

Furthermore, Maximum Power Point Tracking (MPPT) emerges as a critical optimization technology for renewable energy harvesting.

By dynamically modulating the electrical operating locus, it ensures the extraction of peak power from PV modules under varying conditions.

The subsequent chapter provides an in-depth exploration of MPPT methodologies, emphasizing their significance and various implementation strategies in energy-efficient systems.

Chapter 3

Maximum Power Point Tracking

1- Introduction :

To mitigate performance degradation in solar panels and attain peak efficiency, optimizing the design of all photovoltaic (PV) system components is imperative. Furthermore, it is essential to optimize the DC/DC converters acting as the interfacing stage between the PV generator and the load to ensure continuous maximum power extraction. This facilitates operating the PV system at its Maximum Power Point (MPP) through a Maximum Power Point Tracking (MPPT) controller, thereby minimizing transmission energy losses.

Consequently, optimal power output is maintained despite fluctuating load demands and varying atmospheric conditions, specifically solar irradiance and ambient temperature.

Since the 1970s, a vast array of MPPT control strategies has been developed, evolving from fundamental techniques based on voltage and current state feedback to more sophisticated controllers utilizing advanced algorithms for precise MPP computation. Among the most prevalent methodologies are the Incremental Conductance (INC) method, the Perturb and Observe (P&O) technique, and the 'Hill Climbing' approach [11].

❖ Maximum Power Point Tracking :

The enhancement of photovoltaic (PV) system efficiency inherently necessitates the maximization of the power harvested from the PV generator.

This objective is attained through the precise identification of the **optimal operating point**, thereby ensuring impedance matching between the load and the voltage source.

Within this framework, the DC-DC converter functions as an **impedance adapter**, facilitating operation at the ideal point to enable peak power production from the PV generator [12].

Consequently, maximizing the power output of a photovoltaic source involves the continuous pursuit of this optimal operating point a control paradigm formally recognized as **Maximum Power Point Tracking (MPPT)**.

These MPPT methodologies are predicated on **iterative search algorithms** designed to calibrate the solar module's operating point, ensuring that the generated power is maximized without compromising the system's operational continuity.

These techniques are fundamentally based on the perpetual maximization of the instantaneous power generated by the PV modules.

The power extracted is derived from real-time current and voltage measurements, processed through the product of these two physical quantities. Such metrics are utilized by various sophisticated algorithms that strive to track the **True Maximum Power Point (MPP)**.

Among the diverse spectrum of MPPT control strategies, this work highlights the principles of several prominent methods, including the Constant Voltage method, the Constant Current method, the Incremental Conductance (INC) algorithm, and the **Perturb and Observe (P&O)** method. The latter has been implemented in this research due to its robust operational simplicity and ease of hardware execution.

2- Working principle of MPPT :

Specific control laws exist to bring devices to operate at maximum points of their characteristics without these points being known in advance, nor without knowing when they have been modified or what the reasons for this change are. For energy sources, this results in maximum power points.

This type of control is often referred to in the literature as "Maximum Power Point Tracking" or "MPPT" in Anglo-Saxon (MPPT). The principle of these controls is to perform a search for the maximum power point (MPP) while ensuring a perfect adaptation between the generator and its load in order to transfer the maximum power[13].

To simplify the operating conditions of this control, a DC load is chosen. As we can see on this chain, the MPPT control is necessarily associated with a four-pole with degrees of freedom that allow adaptation between the PV generator and the load. In the case of solar conversion, the four-pole can be realized using a DC-DC converter so that the power supplied by the PV generator corresponds to the maximum power (P_{MAX}) that it generates and that it can then be transferred directly to the load.

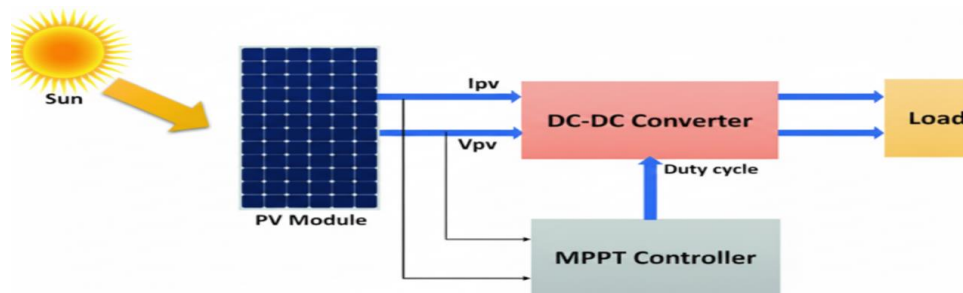


Figure 30: Block Diagram of The PV System

The commonly used control technique is to act on the duty cycle automatically to bring the generator to its optimum operating value because of sudden load variations that can occur at any time. Figure 30 illustrates three (03) sorts of disturbances. Depending on the type of disturbance, the operating point moves from the maximum power point MPP1 to a new operating point P1 more or less far from the optimum. For a variation of sunshine (case a), one needs to adjust the duty cycle value to converge to the new MPP2.

For a load variation (case b), we may note a change in the operating point which can find a new optimum position due to the action of a control. To a lesser extent, the last case of variation of the operating point may occur due to the variations in operating temperature of the photovoltaic module (case c).

Although we have to act at the control level, the latter does not have the same time constraints as the previous two cases[14].

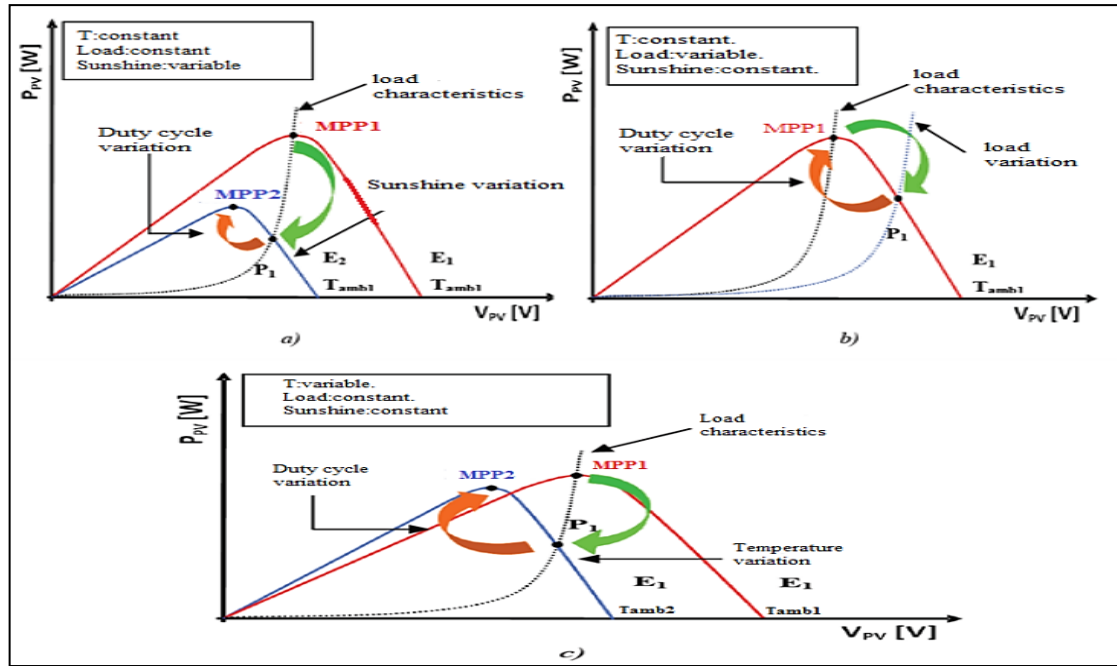


Figure 31: Search and Recovery Of MPP

3- Classification of MPPT Control :

We can generally classify MPPT controllers according to the type of electronic implementation: analogical, digital, or mixed. However, it is more interesting to classify them according to the type of search they perform and the input parameters of the MPPT controller.

3-1- Classification of MPPT Controllers Based on Input Parameters:

3-1-1- MPPT Controllers Operating from Input Parameters:

Various Maximum Power Point Tracking (MPPT) control methodologies primarily rely on analyzing the output power dynamics of photovoltaic (PV) arrays to determine the optimal operating path. Prominent among these techniques are the Perturb and Observe (P&O) and Incremental Conductance (IncCond) algorithms, which utilize real-time power evaluation to implement precise control actions, ensuring system stability at the maximum power point.

Furthermore, a class of controllers has emerged based on the proportional relationships between the optimal operating parameters V_{opt} and I_{opt} and the PV module's characteristic parameters, such as the open-circuit voltage (V_{oc}) and short circuit current (I_{sc}).

This category also encompasses Artificial Neural Network (ANN)-based controller, which function by either employing extensive memory systems to accommodate all possible operating scenarios or utilizing approximation models to estimate required values.

These advanced systems are characterized by their high capability to balance tracking precision with rapid response times to varying environmental conditions [15].

3-1-2- MPPT Controllers Operating from Output Parameters of the Converter:

The literature also identifies a category of algorithms predicated on the output parameters of DC-DC converters.

Notable examples include MPPT controllers designed to maximize the output current, primarily utilized in battery-loading applications.

These systems derive an approximation of the maximum power (P_{max}) based on the converter's efficiency; thus, the approximation's validity is directly proportional to the conversion stage's performance.

Nevertheless, single-sensor systems are inherently characterized by limited precision, as most were originally engineered for specialized aerospace applications [15].

3-2- Classification of MPPT Controllers According to the Type of Search:

3-2-1- Indirect MPPT:

This MPPT control variant exploits the inherent correlation between easily measurable variables (e.g., V_{oc}) and the estimated position of the Maximum Power Point (MPP). It encompasses methodologies predicated on predefined parametric models for operating point estimation, as well as controllers that execute optimal voltage tracking based solely on temperature sensor feedback. While these strategies offer the advantage of low computational complexity and ease of implementation, they are primarily intended for cost-effective, low-precision systems operating in geographically stable climates with minimal environmental fluctuations [16].

3-2-2- Direct MPPT:

This MPPT control variant identifies the optimal operating point by monitoring real-time current, voltage, or power, enabling robust adaptation to stochastic fluctuations in PV system performance.

These methodologies typically employ iterative search algorithms that increment the operating voltage at regular intervals; the search direction is maintained if power increases and reversed otherwise, resulting in steady-state oscillation around the MPP.

To mitigate interpretation errors such as incorrect directional tracking during rapid irradiance ramps advanced algorithms integrate precise power calculations derived from voltage and current measurements.

Alternatively, some techniques introduce small-signal sinusoidal perturbations into the converter's switching frequency to analyze the AC and DC components of the PV voltage, ensuring the operating point remains in close proximity to the MPP.

The primary advantages of these controllers are their superior tracking precision and rapid dynamic response [16].

4- Different MPPT Controls Synthesis :

Since the inaugural publication of a dedicated control law for renewable energy systems (photovoltaic) in 1968, the scientific literature has seen a continuous evolution of Maximum Power Point Tracking (MPPT) strategies.

Given the extensive proliferation of research in this domain, it is essential to establish a systematic classification of these techniques based on their underlying theoretical frameworks and operational principles.

4-1- First MPPT Controls Types:

The initial algorithms developed for Maximum Power Point Tracking (MPPT) were characterized by their structural simplicity, primarily due to the limited computational capacity of early microcontrollers and the less stringent dynamic requirements of early aerospace applications. The pioneering work in this field is attributed to A.F. Boehringer, who introduced a control law based on adaptive control to maintain the system at its Maximum Power Point (MPP).

As illustrated in Figure 3, the operational principle relies on calculating the instantaneous power at time t_i using measured V_{pv} and I_{pv} values, followed by a comparison with the preceding value stored at T_{i1} .

This differential then dictates the adjustment of the duty cycle (D) applied to the static converter.

While this foundational principle remains theoretically robust and widely integrated into modern numerical algorithms, contemporary advancements have significantly enhanced both response time and tracking accuracy [14].

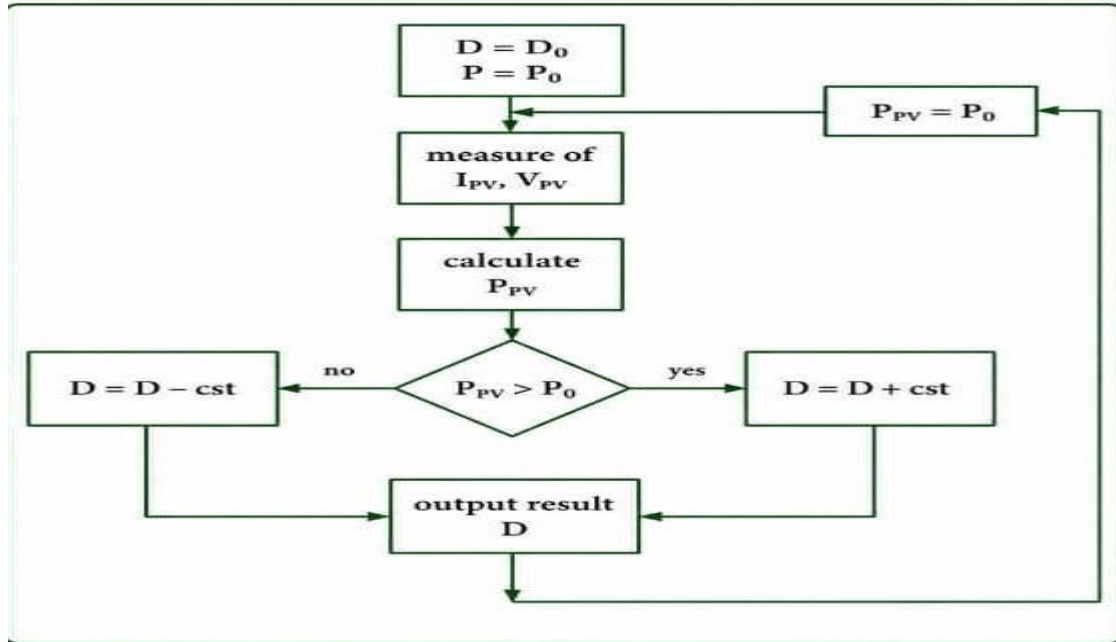


Figure 32: Bloc Diagram of a Digital MPPT Control

4-2- Efficient MPPT Controls Algorithms :

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

4-3- Algorithm Perturb and Observe (P&O) :

The P&O algorithm tracks the Maximum Power Point (MPP) through iterative voltage perturbations (ΔV). Based on the resultant power fluctuation (ΔP), as depicted in Figure 32, the system determines its position relative to the MPP: a positive gradient ($\Delta P / \Delta V > 0$) indicates the operating point is to the left of the MPP, while a negative gradient signifies it has been exceeded.

Consequently, the algorithm adjusts the perturbation direction to converge toward and maintain the optimal power output.

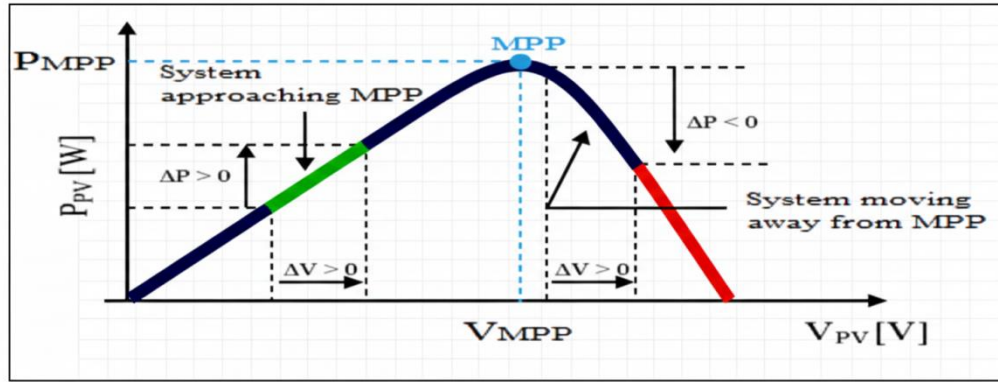


Figure 33: Ppv VS Vpv Characteristic of a Solar Panel

Figure (III.5) The conventional method for Maximum Power Point Tracking (MPPT) using the Perturb and Observe (P&O) algorithm relies on analyzing the variation in power resulting from each voltage disturbance. This approach requires two sensors one for current and one for voltage in order to accurately calculate the instantaneous power of the solar generator.

The P&O technique is widely adopted due to its simplicity and ease of implementation. Nevertheless, it suffers from a key limitation: oscillations around the maximum power point (MPP) during steady-state operation. This occurs because the search for the MPP must be repeated periodically, leading to continuous fluctuations in system performance around the optimal point and reducing overall energy conversion efficiency.

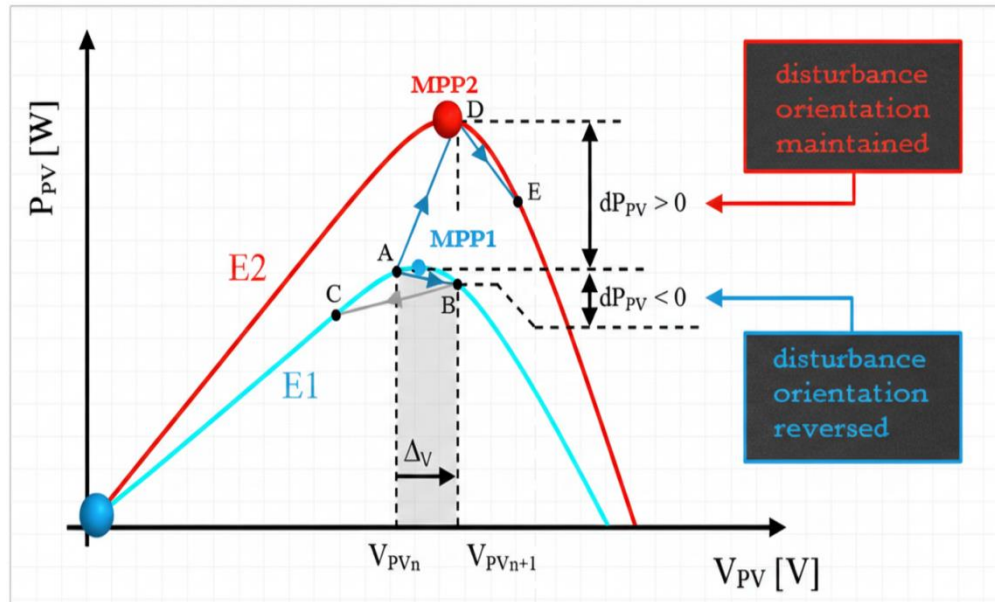


Figure 34: Divergence of The P & O Control Due to Radiation Variations

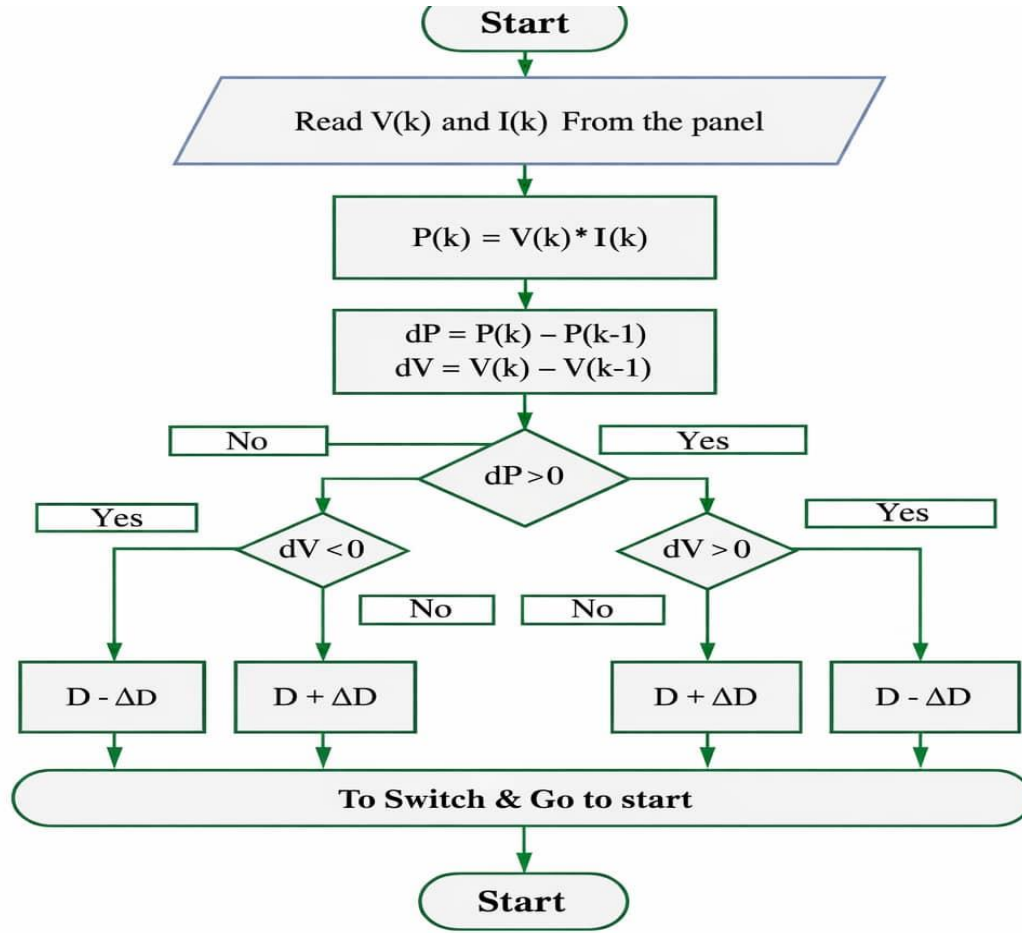


Figure 35: Algorithm of The P & O Type of Control

To clarify the operation of the Perturb & Observe MPPT algorithm, consider a solar module under irradiation level (E_1), with its operating point initially at A, when a voltage disturbance (ΔV) is applied, the operating point shifts to B. Since illumination remains unchanged, this shift produces a negative derivative of power, reversing the sign of the perturbation, as a result, the operating point oscillates between B and C, creating fluctuations around the Maximum Power Point (MPP).

The magnitude of power transfer losses during these oscillations depends on the relative positions of B and C with respect to A, when irradiation changes from (E_1) to (E_2), the operating point moves from A to D, In this case, the algorithm interprets the shift as a positive variation in power, guiding the system toward the new MPP[14].

❖ **Algorithm Hill Climbing :**

The fundamental advantage of the Hill Climbing MPPT method lies in its operational simplicity, utilizing the boost converter's duty cycle as the primary feedback parameter during the tracking process [17], [18], However, the primary structural drawback of this technique

arises from the inherent trade-off between system stability during periods of constant irradiation and the necessity for a rapid dynamic response [17], [18]. Under steady-state irradiation, the system requires an infinitesimal variation in the duty cycle (ΔD) to mitigate power oscillations around the peak point, thereby maximizing energy extraction from the PV array. Conversely, transient conditions with rapidly fluctuating irradiation necessitate a higher duty cycle step size to accelerate the pursuit of the maximum power point.

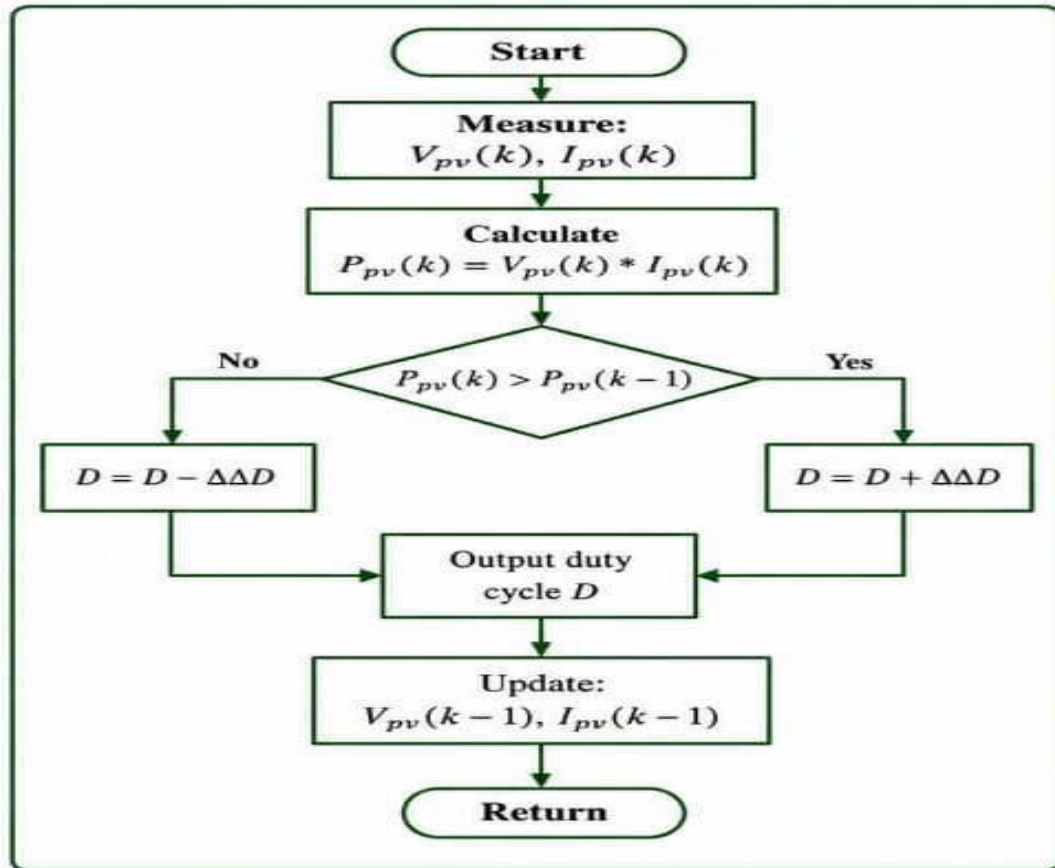


Figure 36: State Flowchart of Hill Climbing MPPT Technique

4-4- Algorithm Incremental conductance (INC):

This algorithm leverages the analytical comparison between instantaneous conductance (I/V) and incremental conductance (dI/dV) to locate the operating point relative to the Maximum Power Point (MPP). By modulating the duty cycle, the system dynamically tracks the MPP: if $dI/dV > -I/V$, the duty cycle is decreased to increment the operating voltage, whereas it is increased to reduce the voltage if $dI/dV < -I/V$. This iterative optimization continues until the equilibrium condition ($dI/dV = -I/V$) is satisfied, ensuring the system operates at peak power efficiency [19].

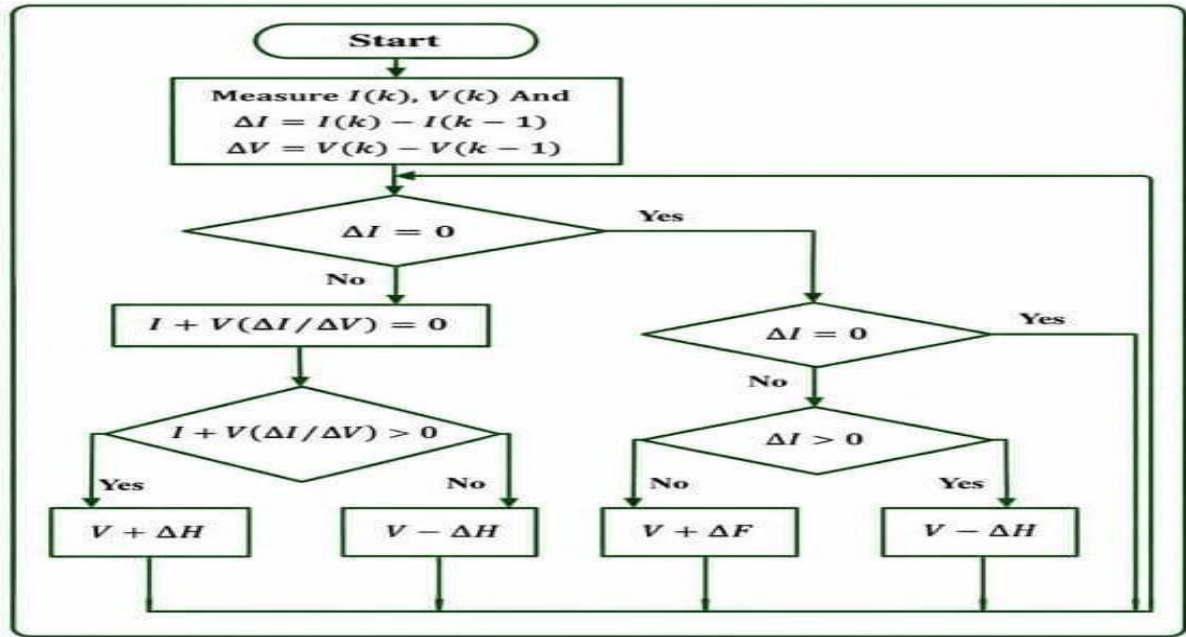


Figure 37: Flowchart for The Incremental Conductance Algorithm.

4-5- Artificial Neural Networks (ANN):

Broadly defined, Artificial Neural Networks (ANNs) utilize a parallel processing architecture comprised of numerous computational units organized into distinct hierarchical layers. The input layer is responsible for the ingestion of raw data, functioning analogously to the biological transmission of visual stimuli via the optic nerves in the human physiological system.

Subsequently, each successive layer receives and processes the transformed outputs from its predecessor. This iterative mechanism emulates the human neural process, wherein biological neurons relay electrochemical signals originating from those proximal to the optic nerve. Ultimately, the output layer synthesizes these computations to generate the system's definitive results or predictive inferences.

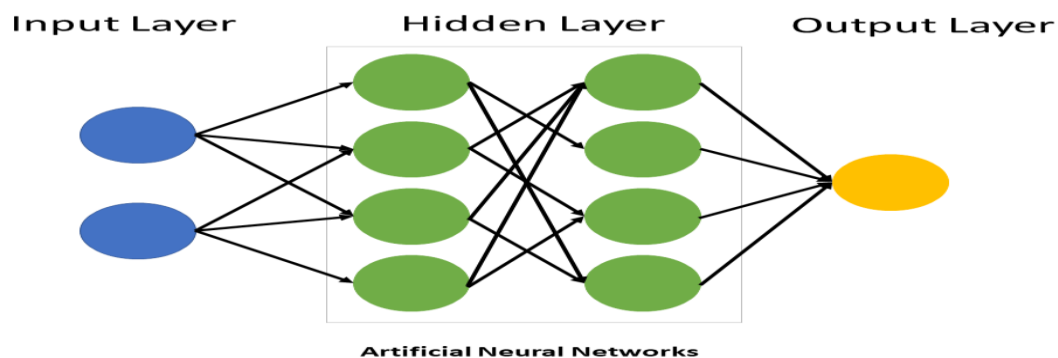


Figure 38: Functioning of Artificial Neural Networks

Neural networks facilitate autonomous pattern recognition and data synthesis through sophisticated algorithms, emulating biological cognitive development rather than traditional procedural programming. Their learning architectures are categorized into three primary paradigms:

1. **Supervised Learning:** The algorithm is trained on labeled datasets, iteratively adjusting parameters to align model outputs with target benchmarks.
2. **Unsupervised Learning:** The network autonomously identifies latent structures within unlabeled data, utilizing a cost function as a heuristic to measure and minimize deviations from the objective.
3. **Reinforcement Learning:** Performance is optimized via a reward/penalty mechanism, enabling the system to refine its decision-making trajectories cumulatively through trial and error.

4-6- Application of Artificial Neural Networks in MPPT :

Artificial Neural Networks (ANNs) are increasingly integrated into Photovoltaic (PV) systems to optimize Maximum Power Point Tracking (MPPT) through their superior handling of non-linear environmental stochasticity. By autonomously mapping complex inputs such as solar irradiance, ambient temperature, and partial shading ANN-based controllers dynamically recalibrate the operating point to maintain peak power extraction. This methodology significantly enhances conversion efficiency and overall energy yield, underscoring the pivotal role of computational intelligence in advancing the performance and robustness of PV power generation[20].

5- Implementation of ANN in MATLAB/SIMULINK :

The Neural Network Fitting app in MATLAB serves as a sophisticated computational framework, providing a high-fidelity interface for the synthesis, training, and performance validation of artificial neural networks. The procedural workflow necessitates a meticulous selection of datasets, followed by the strategic configuration of the network architecture and iterative training cycles. The efficacy of the resultant model is subsequently rigorously appraised through a multifaceted array of diagnostic plots and statistical metrics. This tool is of paramount importance in applications such as Maximum Power Point Tracking (MPPT), where the primary objective is the high-precision modeling of highly non-linear and stochastic input-output relationships.

5-1- Data Acquisition and Pre-processing:

The foundational phase of the proposed methodology entails the systematic extraction of empirical data from MPPT simulations across a diverse spectrum of operational scenarios and environmental contingencies. Robust data collection serves as the empirical cornerstone, ensuring the representational integrity required for the training and objective evaluation of the ANN-based MPPT paradigm [20].

5-2- Configuration and Calibration of the Neural Network Fitting Tool:

To initiate the implementation trajectory, the Neural Network Fitting Tool is deployed within the MATLAB environment, offering a robust analytical platform for network refinement. This stage involves the seamless integration of pre-defined variables and the bespoke configuration of the tool's parameters to align with the specific technical constraints and physical exigencies of the application under investigation [21].

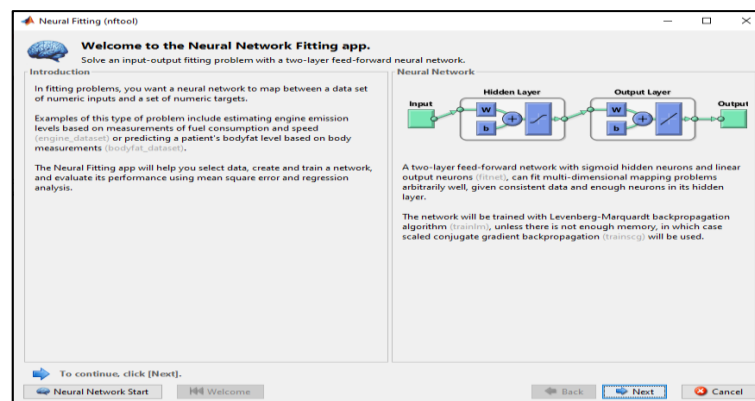


Figure 39: Setting Up the Neural Network Fitting Tool

This figure illustrates the Neural Network Fitting application, detailing its primary objective: addressing input-output mapping problems through the implementation of a two-layer feed-forward neural architecture. The application is designed to model the underlying relationship between a set of input vectors and their corresponding target values.

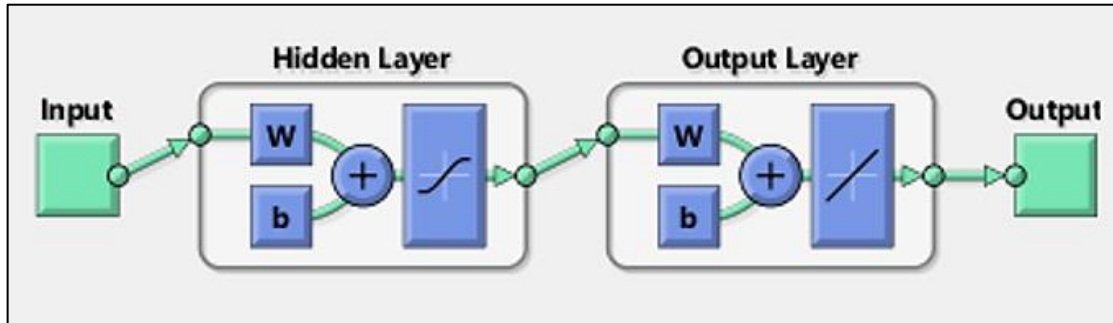


Figure 40: Neural Network Structure

The schematic delineates the structural configuration of the neural network, which comprises an input layer, hidden layers, and an output layer.

Training Methodology: The text specifies that the network undergoes optimization via the Levenberg-Marquardt backpropagation algorithm, computationally referenced as (`trainlm`).

5-2-1- Select Data:

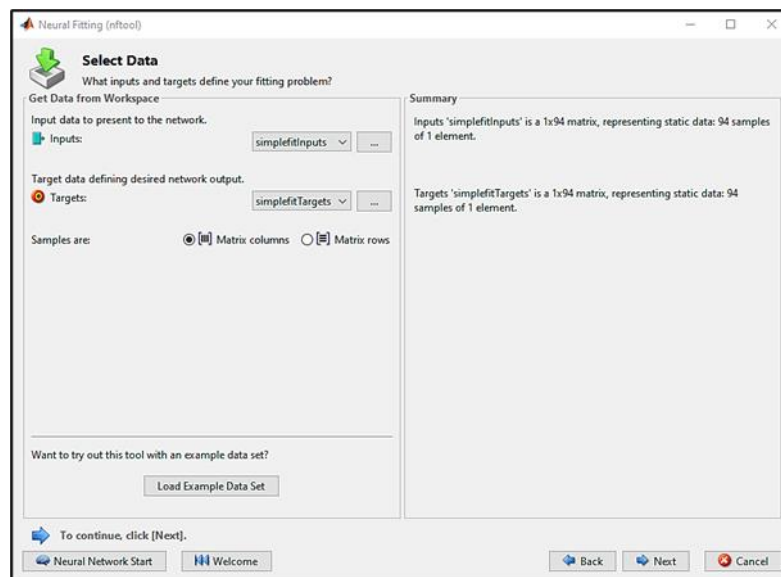


Figure 41: Select Data

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.

5-2-2- Import Data:

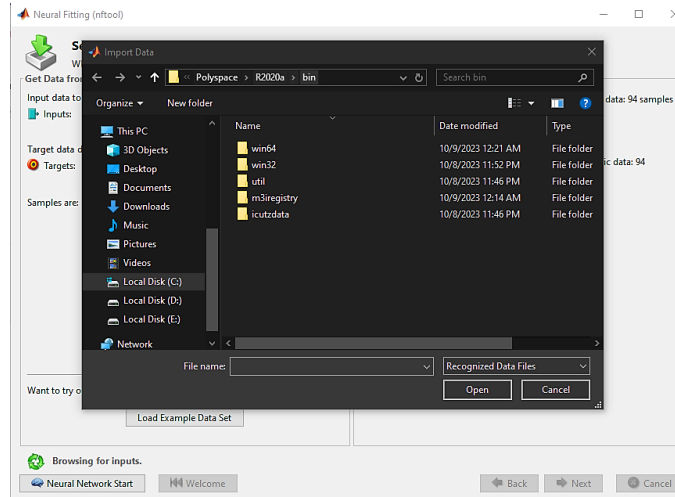


Figure 42: Import Data

Data Importation: In instances where the required datasets are not pre-resident within the MATLAB workspace, this interface facilitates the external browsing and ingestion of data files from local storage. This procedural step is critical to ensure that the input and target matrices are accurately instantiated within the environment, thereby establishing a robust foundation for the subsequent neural network training phase.

5-2-3- Validation and Test Data:

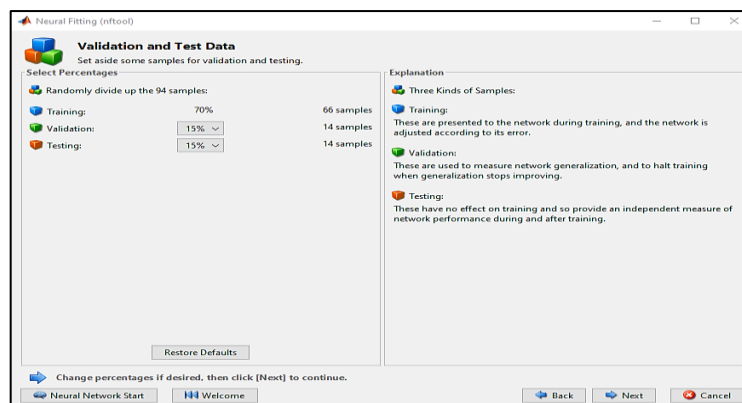


Figure 43: Validation and Test Data

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.

5-2-4- Network Architecture:

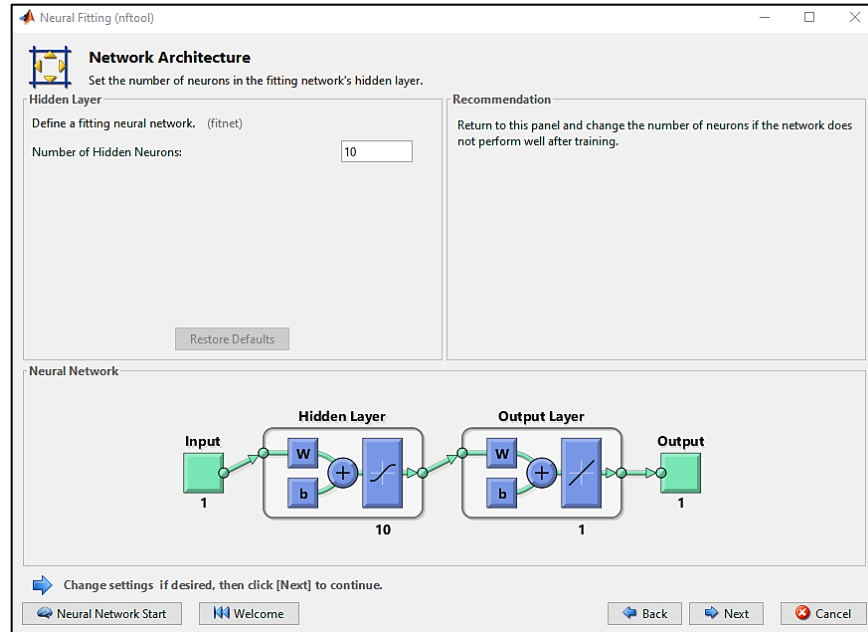


Figure 44: Network Architecture

Hidden Layer Parameterization: This interface facilitates the quantitative determination of the neuronal count within the hidden layer(s)[17], In this specific implementation, the architectural complexity is defined by a single hidden layer comprising ten (10) discrete neurons.

Topological Representation: The diagrammatic output provides a high-fidelity visualization of the network's internal structure, explicitly illustrating the integration of the specified hidden neurons and their functional connectivity within the overall system architecture.

5-2-5- Network Training:

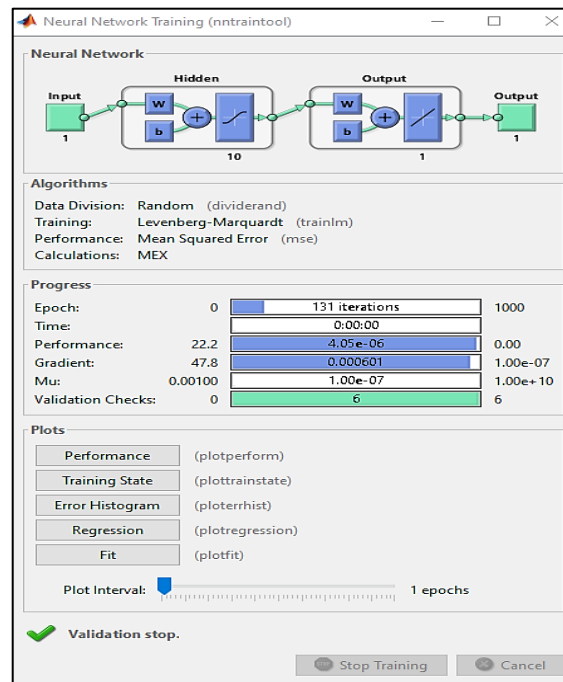


Figure 45: Network Training

- **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].

5-2-6- Train Network :

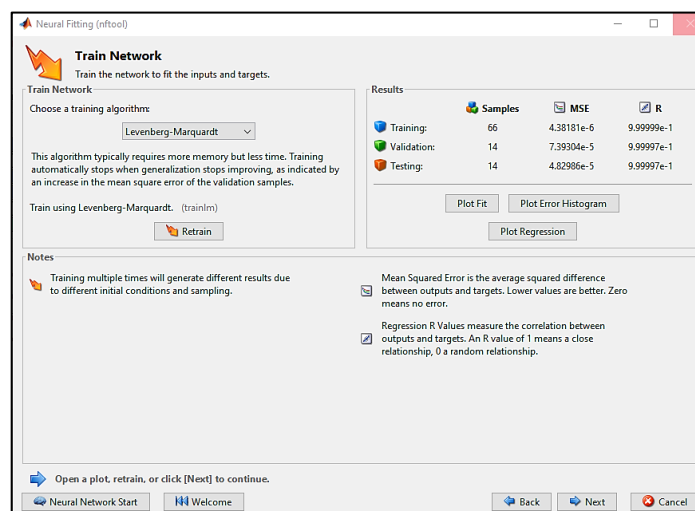


Figure 46: Train Network

- **Quantitative Performance Metrics:** Post-training, this interface delineates the empirical results, specifically the **Mean Squared Error (MSE)** calculated across the training, validation, and testing datasets.
- **Correlation and Regression Analysis:** The regression plot illustrates the statistical correlation between the network's predictive outputs and the defined target values. A high **R-value** approaching unity (1) signifies an optimal functional fit and robust model generalization.
- **Residual Error Distribution:** The error histogram provides a graphical representation of the distribution of residuals between the synthesized outputs and the ground-truth targets [22].

6- Conclusion:

This chapter addresses the critical and highly specialized core of the study, presenting the fundamental principles and classification of Maximum Power Point Tracking (MPPT) methodologies. By examining the most prevalent MPPT techniques in existing literature, it becomes evident that the diversity of these control strategies underscores a continuously evolving research landscape. This proliferation further highlights the inherent difficulty in establishing a singular, universal solution capable of addressing all operational constraints across varying PV systems.

Chapter 4

Simulation Results

1- Introduction :

In this chapter, a comprehensive performance evaluation and comparative analysis of three widely used Maximum Power Point Tracking (MPPT) techniques are presented, namely the Perturb and Observe (P&O) algorithm, the Incremental Conductance (INC) algorithm, and approaches based on Artificial Neural Networks (ANN). MPPT algorithms play a fundamental role in improving the efficiency of photovoltaic (PV) systems by dynamically adjusting the operating point to ensure the extraction of the maximum available power from solar panels under varying environmental conditions. Accurate tracking of the maximum power point significantly contributes to enhancing energy conversion efficiency and the overall operational performance of PV systems. The Perturb and Observe method determines the optimal operating point by introducing periodic perturbations and observing the resulting variations in power, whereas the Incremental Conductance method relies on the relationship between incremental conductance and instantaneous conductance to achieve more precise tracking, particularly under changing solar irradiance conditions. In contrast, Artificial Neural Network based techniques utilize artificial intelligence and learning capabilities to predict and track the maximum power point with a high level of accuracy and adaptability. This study therefore aims to conduct a detailed comparative evaluation of these algorithms in order to identify their respective advantages and limitations, thereby providing deeper insights into their performance characteristics and highlighting their suitability for different operating conditions in photovoltaic energy conversion systems.

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 47: Characteristics of Panel

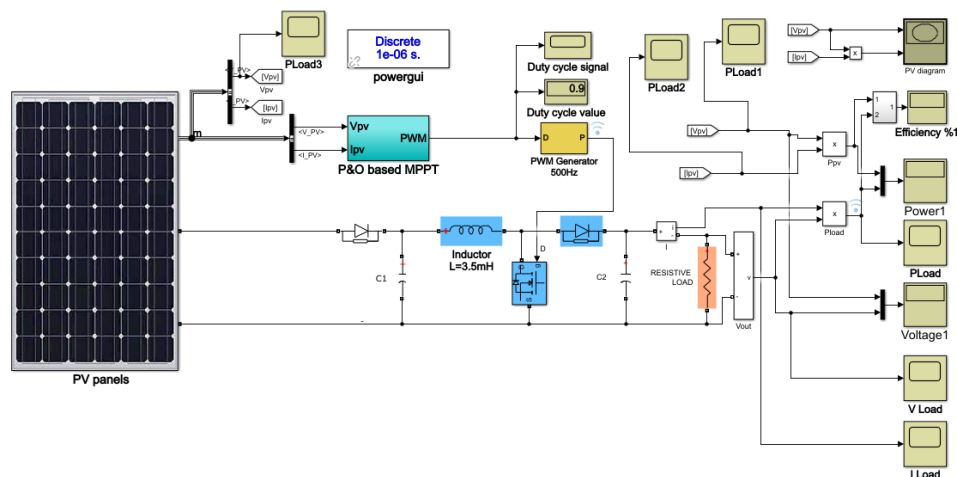
Table 3: Parameters of Boost Converter

Boost Converter	Value
Capacitor 1	200 μ F
Inductor	3.5 mH
Capacitor 2	100 μ F
Resistive Load	300 Ω

3- Simulation Results :

3-1- P&O Algorithm :

In this simulation, we used the Perturb and Observe (P&O) algorithm to obtain results for power, voltage, and current. Figure 48 represents the general system simulation, showcasing the overall setup and performance of the P&O -based MPPT system. The figure illustrates the integration of PV panels with the P&O -based MPPT controller, which adjusts the duty cycle to optimize power extraction.

**Figure 48: Schema of System Simulation With P&O**

3-1-1- Constant Irradiance (1000 W/m²):

The Figure 49 demonstrates the MPPT system's duty cycle behavior, with the main plot showing overall stability and the zoomed-in view revealing critical fluctuations for precise MPPT operation.

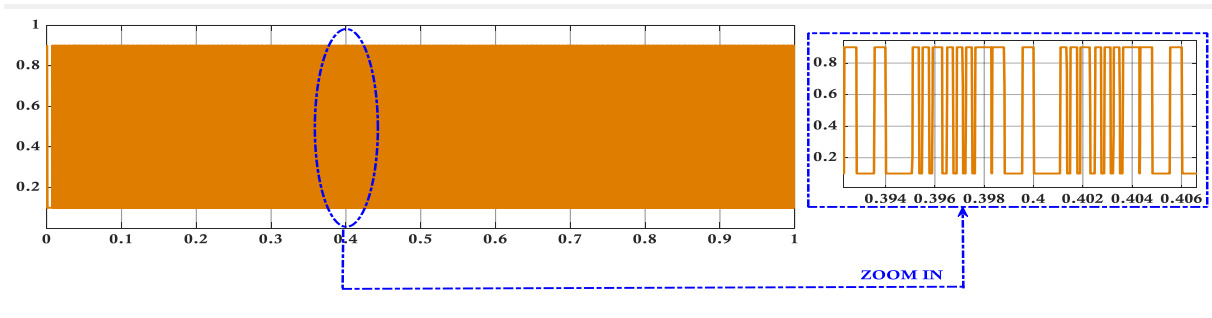


Figure 49: Duty Cycle Simulation Result

Figure 50 illustrates the simulated power response of the MPPT system using the P&O algorithm. The output power rapidly increases and stabilizes around 350 W, indicating successful tracking of the maximum power point. The zoomed view reveals small oscillations around the operating point, which are inherent to the P&O method due to its continuous perturbation process.

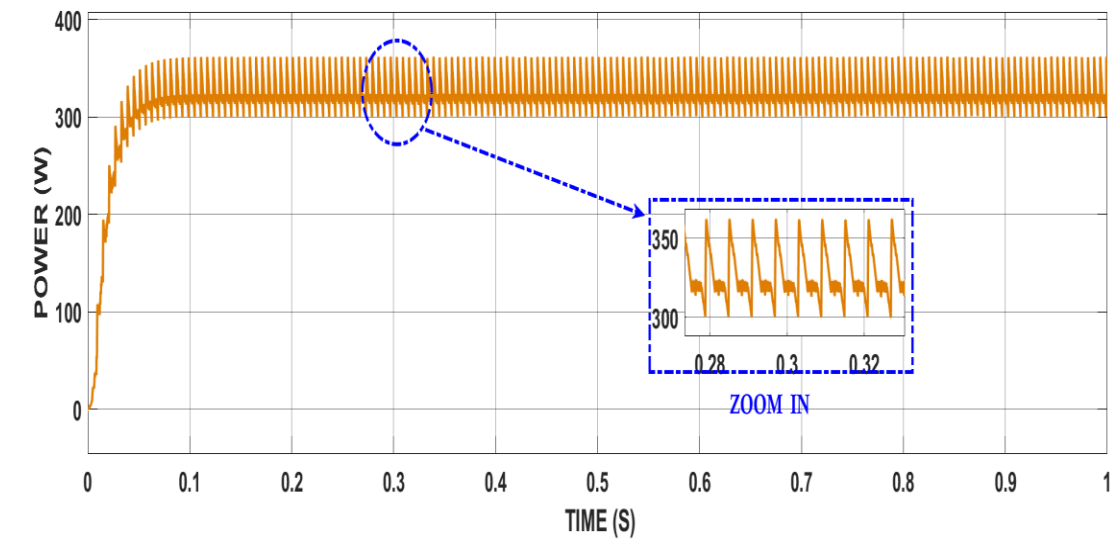


Figure 50: Power Simulation Result

Figure 51 illustrates the voltage response of the MPPT system using the P&O algorithm. The voltage rapidly increases at the beginning of the simulation and stabilizes around 320 V, indicating successful convergence to the optimal operating point. The zoomed view highlights small oscillations around this value, which are inherent to the P&O algorithm due to its continuous perturbation mechanism.

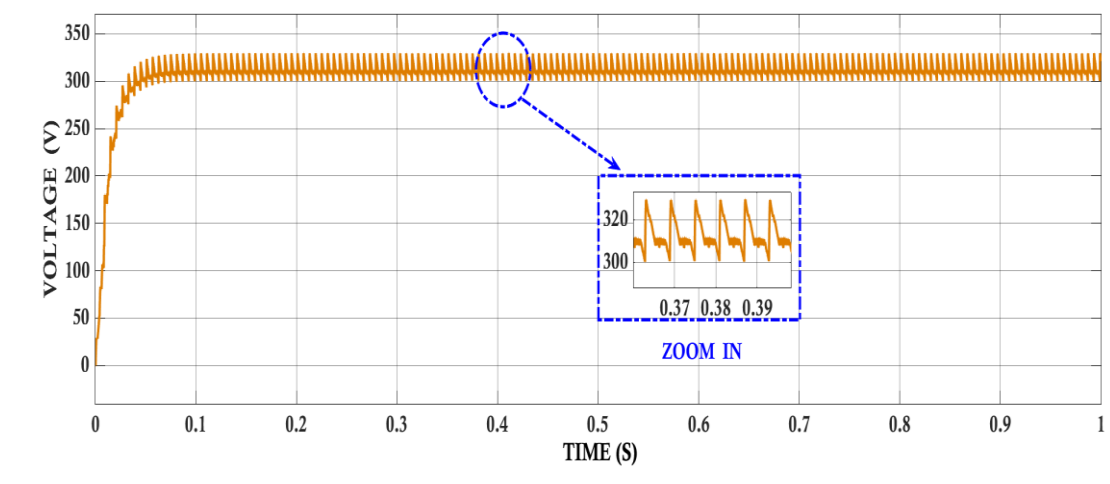


Figure 51: Voltage Simulation Result

Figure 52 presents the simulated current response of the MPPT system employing the Perturb and Observe (P&O) algorithm. As illustrated in the main plot, the current exhibits a fast transient response during the initial period, followed by convergence toward a steady-state value of approximately 1.05 A, indicating that the system has successfully reached the maximum power point (MPP). The enlarged view highlights the small oscillatory behavior around this steady-state operating point, which represents the inherent characteristic of the P&O tracking mechanism during steady-state operation.

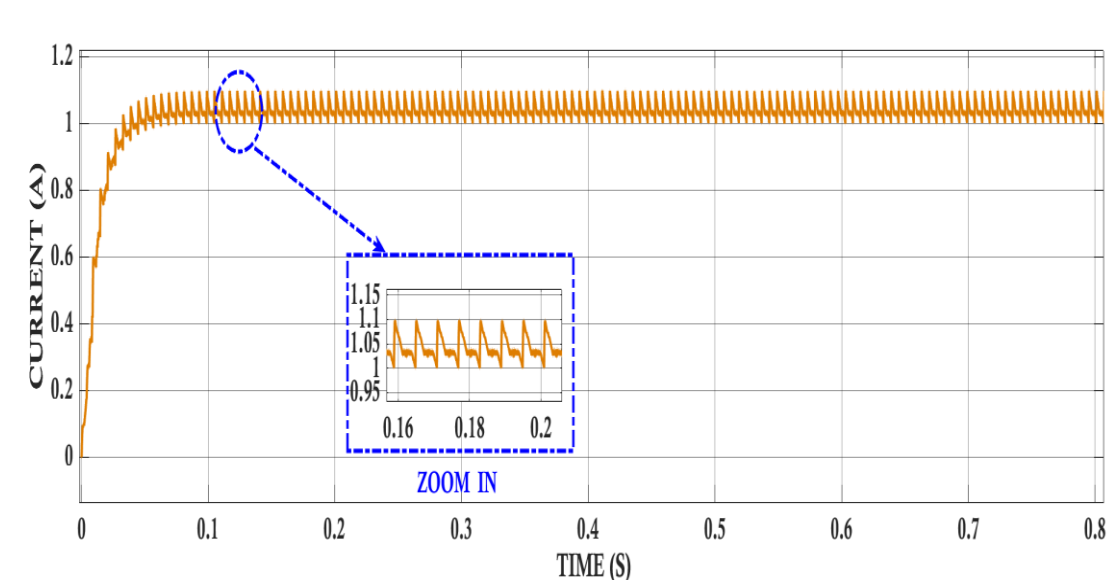


Figure 52: Current Simulation Result

3-1-2-Variable Irradiances (1000, 800, 700, 900W/m²) :

Figure 53 illustrates the output power behavior of the Maximum Power Point Tracking (MPPT) system based on simulation results under varying solar irradiance levels. The curve demonstrates the system's ability to respond effectively to changes in irradiance while maintaining operation close to the maximum power point. The results indicate that the extracted power stabilizes at approximately 350 W, 300 W, 250 W, and 200 W for irradiance levels of 1000, 800, 600, and 400 W/m², respectively. The figure also shows a short transient response following each sudden change in irradiance, after which the system rapidly converges to a new steady operating point. The zoomed-in section highlights small oscillations around the steady-state value, which is a typical characteristic of MPPT systems employing iterative search techniques to track the maximum power point. efficiency and adaptability of the MPPT system in real-time solar energy applications.

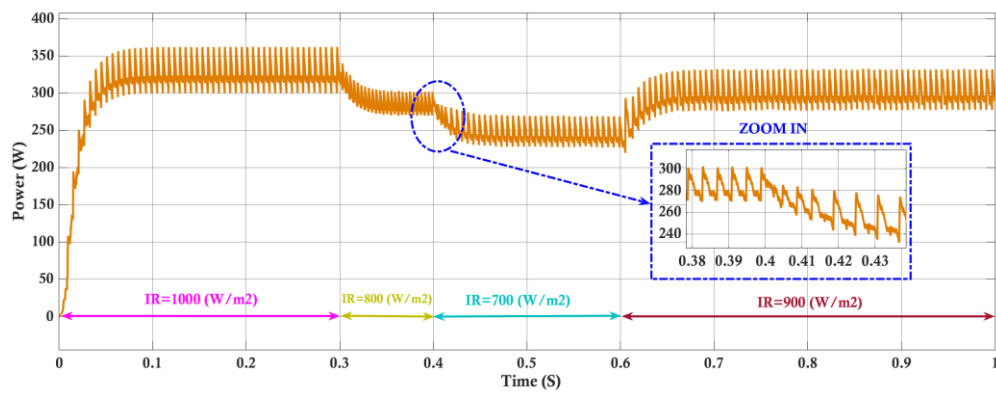


Figure 53: Power Simulation Result

Figure 54 illustrates the simulated voltage response of an MPPT system based on the P&O algorithm under varying solar irradiance levels. The curve shows that the voltage quickly stabilizes around 320 V and then gradually decreases as the irradiance decreases. The zoomed section also highlights small oscillations around the operating point, reflecting the continuous tracking process to maintain optimal system performance.

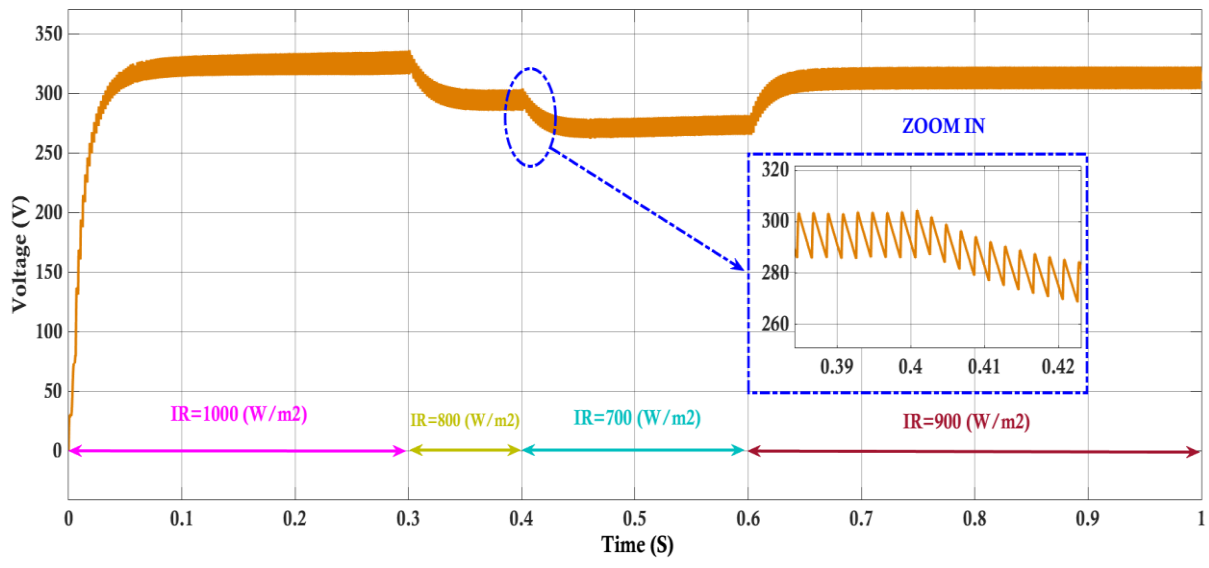


Figure 54: Voltage Simulation Result

Figure 55 illustrates the simulated current response of the MPPT system based on the P&O algorithm under varying solar irradiance levels. The current quickly stabilizes around 1 A and then gradually decreases as the irradiance decreases. The zoomed-in section shows small oscillations around the operating point, indicating the continuous tracking process used to maintain optimal system performance.

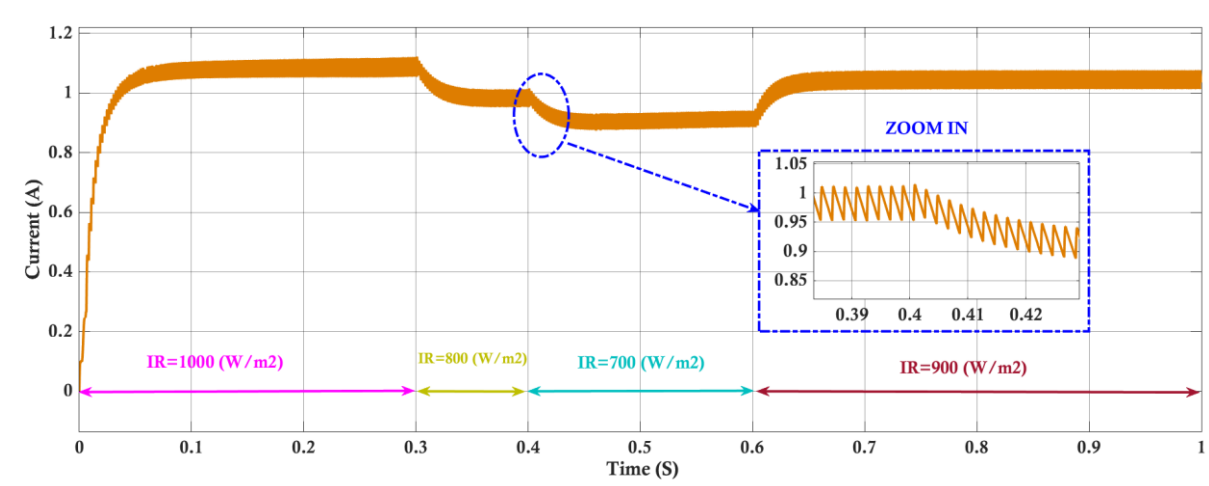


Figure 55: Current Simulation Result

3-2- Incremental Conductance :

In this simulation, we used the Incremental Conductance (INC) algorithm to obtain results for power, voltage, and current. Figure (IV.10) represents the general system simulation, showcasing the overall setup and performance of the INC-based MPPT system. The figure

illustrates the integration of PV panels with the INC-based MPPT controller, which adjusts the duty cycle to optimize power extraction.

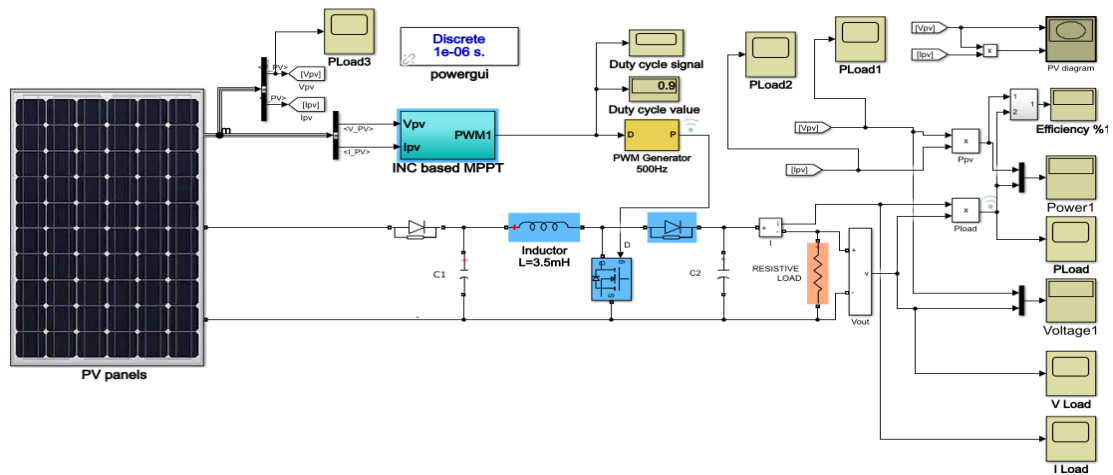


Figure 56: Schema of System Simulation With INC

3-2-1-Constant Irradiance (1000 W/m²):

Figure 57 illustrates the power response of the MPPT system using the Incremental Conductance algorithm. The output power rapidly increases and stabilizes around 370 W, indicating effective tracking of the maximum power point. The zoomed section reveals small periodic oscillations caused by the algorithm's continuous adjustments to maintain operation near the optimal power point confirming the stability of the MPPT control. strategy.

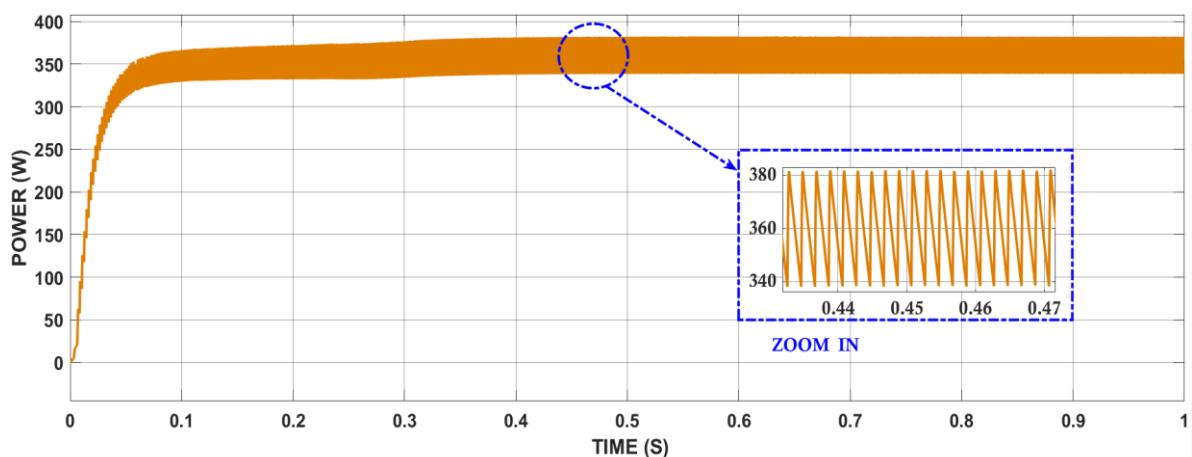


Figure 57: Power Simulation Result

Figure 58 illustrates the simulated voltage response of a photovoltaic system controlled by an Incremental Conductance (INC) based Maximum Power Point Tracking (MPPT) algorithm. The results show that the output voltage rapidly increases during the transient phase and subsequently stabilizes around 330 V in steady-state conditions. The enlarged section highlights the presence of minor oscillations around the operating point, which are characteristic of MPPT tracking behavior and indicate continuous adjustment of the system to maintain operation near the maximum power point.

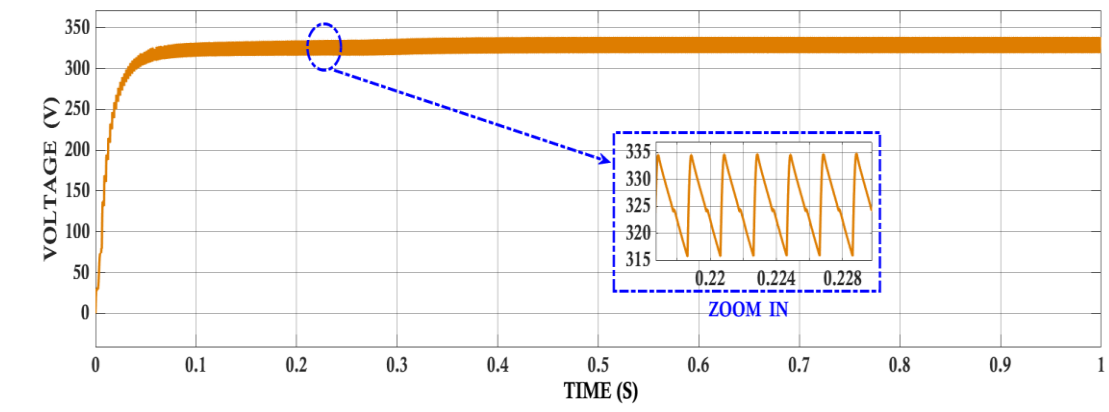


Figure 58: Voltage Simulation Result

Figure 59 presents the simulated current response of the photovoltaic system controlled by the Incremental Conductance (INC) based MPPT algorithm. As illustrated in the main graph, the current rapidly increases during the transient period and then converges to a steady value of approximately 1.1 A, demonstrating the effectiveness of the MPPT controller in driving the system toward the maximum power operating point. The magnified section reveals small oscillatory variations around the steady-state value, which are typical of MPPT tracking processes and reflect the continuous adjustment of the control algorithm.

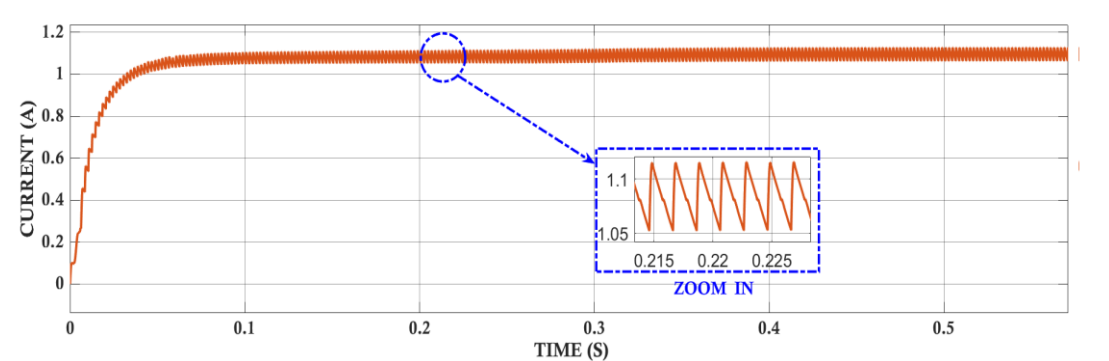


Figure 59: Current Simulation Result

3-2-2- Variable Irradiances (1000, 800, 700, 900W/m²):

Figure 60 illustrates the power response of the MPPT system using the Incremental Conductance algorithm under changing irradiance levels. The output power initially stabilizes near 350 W, then decreases as the irradiance drops, and increases again when the irradiance rises. The zoomed view highlights the small oscillations occurring during the irradiance transition.

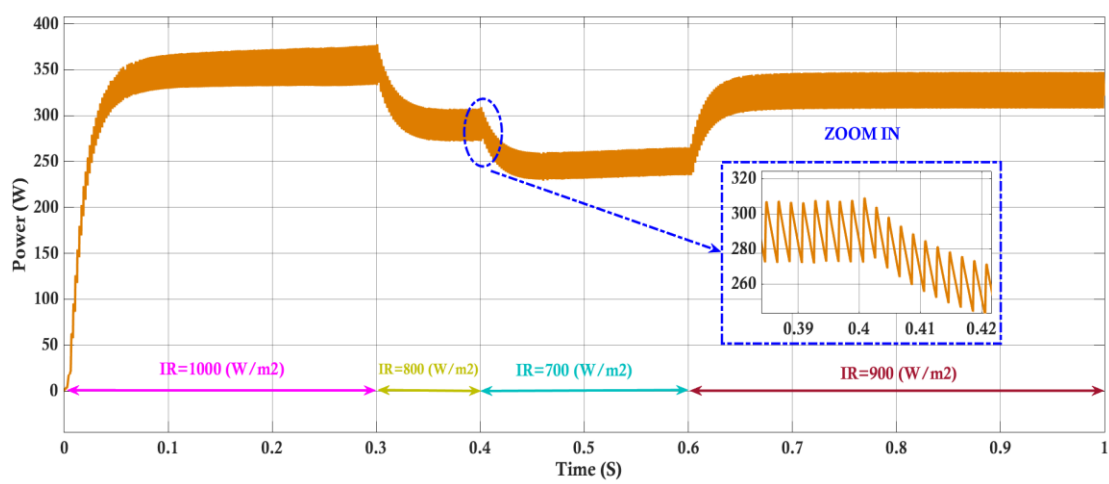


Figure 60: Power Simulation Result

Figure 61 shows the voltage response of the MPPT system using the Incremental Conductance algorithm under varying irradiance conditions. The voltage initially stabilizes around 330 V, then decreases as the irradiance drops, and increases again when the irradiance rises. The zoomed view highlights the small transient oscillations during the irradiance transition.

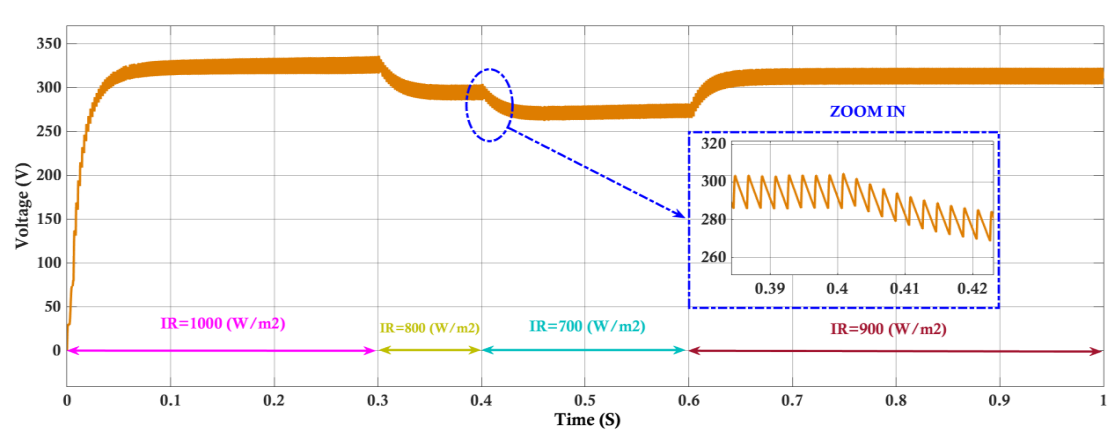


Figure 61: Voltage Simulation Result

Figure 62 shows the current response of the MPPT system using the Incremental Conductance algorithm under varying irradiance. The current initially stabilizes around 1.1 A, then decreases as irradiance drops, and rises again when irradiance increases. The zoomed view highlights the transient fluctuations during the irradiance change.

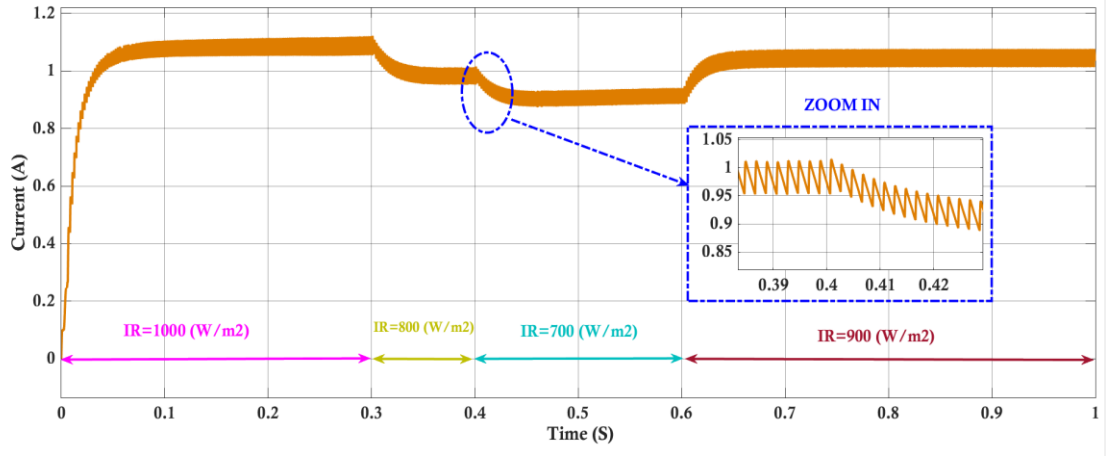


Figure 62: Current Simulation Result

3-3- Artificial Neural Network (ANN):

In this simulation, we used the Artificial Neural Network (ANN) algorithm to obtain results for power, voltage, and current. Figure 63 represents the general system simulation, showcasing the overall setup and performance of the ANN-based MPPT system. The figure illustrates the integration of PV panels with the ANN-based MPPT controller, which adjusts the duty cycle to optimize power extraction.

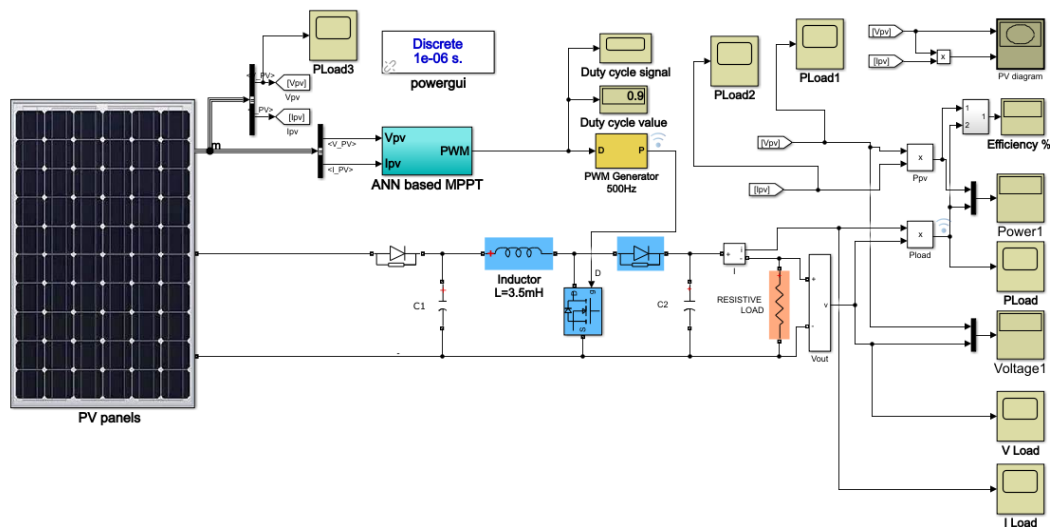


Figure 63: Schema of System Simulation With ANN

3-3-1- Constant Irradiance (1000 W/m²) :

The Figure 64 demonstrates the stability and fine-tuning of the duty cycle by an ANN-based MPPT system. The main plot shows a stable duty cycle near 1, while the zoomed-in view reveals periodic adjustments, indicating the ANN's responsiveness to optimize performance

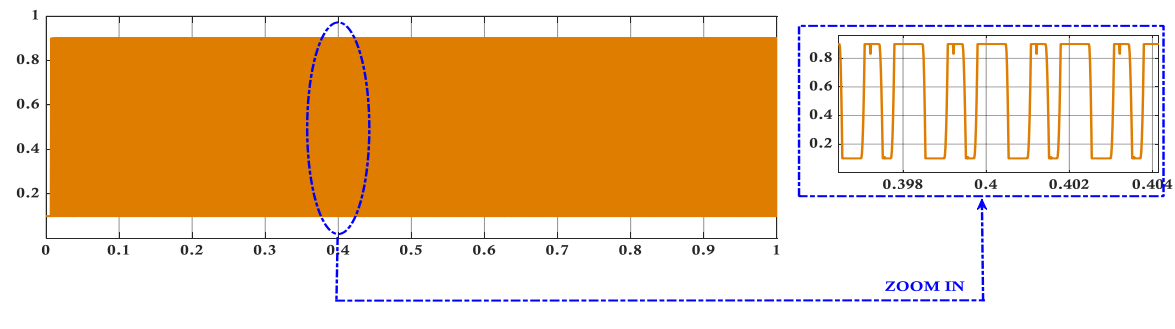


Figure 64: Duty Cycle Simulation Result

Figure 65 illustrates the power response of the MPPT system based on an Artificial Neural Network (ANN). The output power rapidly increases from the initial state and stabilizes around 380 W, indicating the system's effectiveness in tracking the maximum power point. The zoomed view also shows small oscillations around the optimal operating point due to the continuous tracking process performed by the control algorithm.

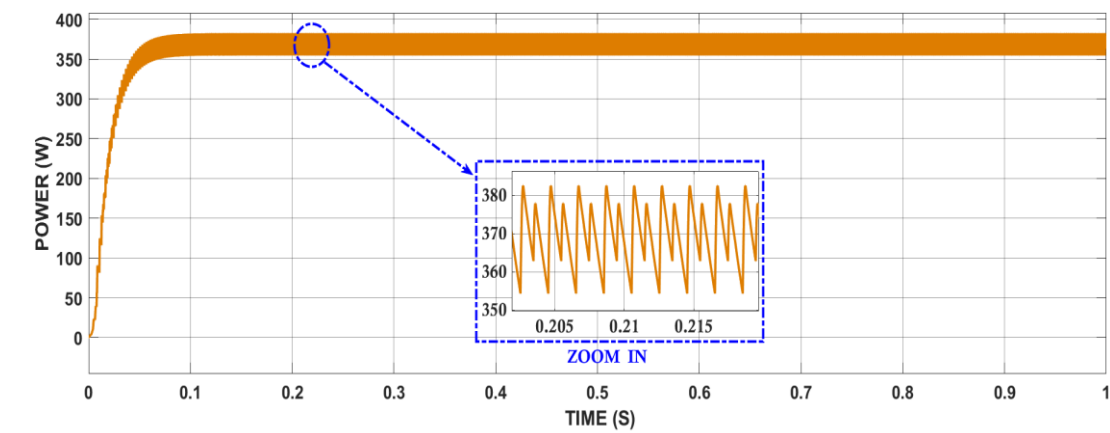


Figure 65: Power Simulation Result

Figure 66 illustrates the voltage response of the ANN-based MPPT system. The voltage rapidly rises from the initial state and stabilizes at approximately 335 V, indicating the effectiveness of the control strategy. The zoomed-in view also shows small oscillations around the steady-state value due to the continuous maximum power point tracking process.

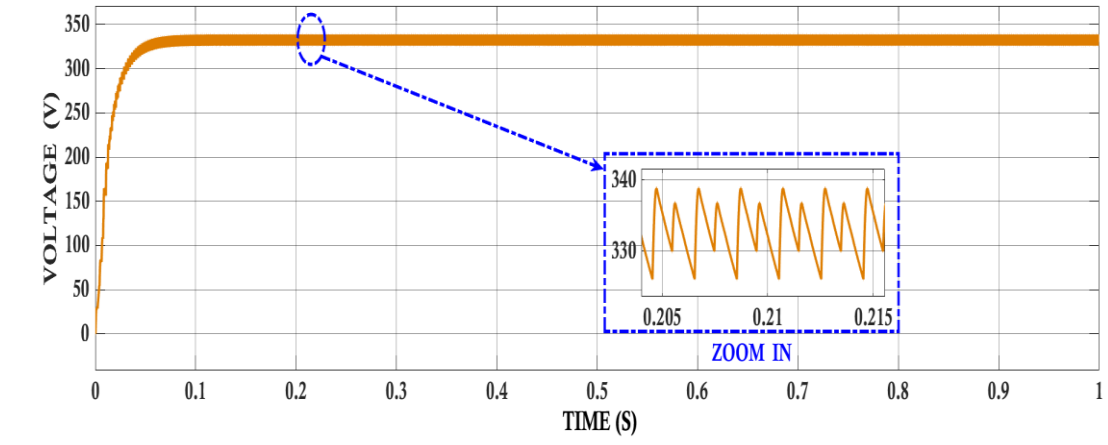


Figure 66: Voltage Simulation Result

Figure 67 illustrates the current response of the ANN-based MPPT system. The current rises rapidly and stabilizes around 1.1 A, indicating effective system convergence. The zoomed view shows small oscillations around the steady-state value, which remain within an acceptable range and confirm the stability of the system .

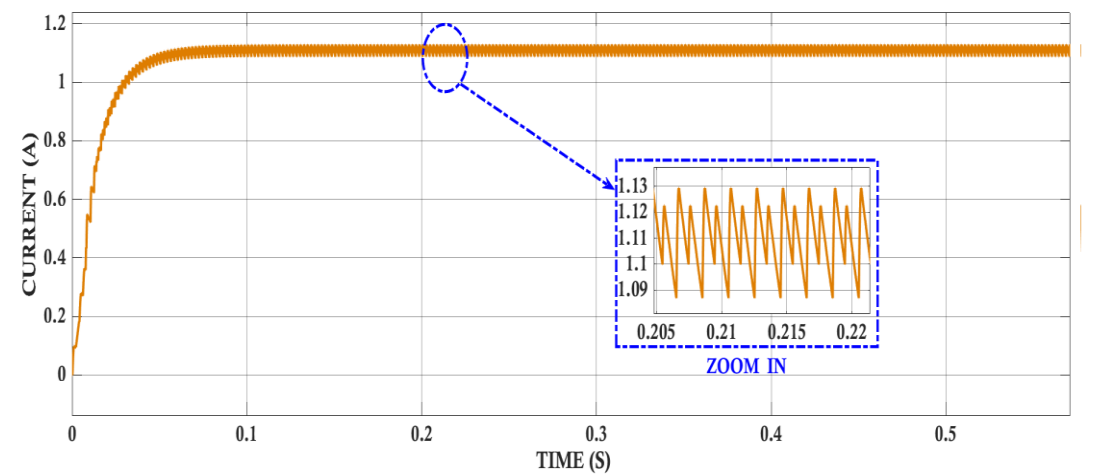


Figure 67: Current Simulation Result

3-3-2-Variable Irradiances (1000, 800, 700, 900W/m²):

Figure 68 presents the power response of the ANN-based MPPT system under varying irradiance levels. Initially, the output power rapidly reaches a steady value close to 350 W. As the irradiance changes, the power follows these variations with corresponding step changes, demonstrating the system's capability to track the maximum power point effectively. The zoomed section highlights small transient oscillations occurring during the irradiance transition.

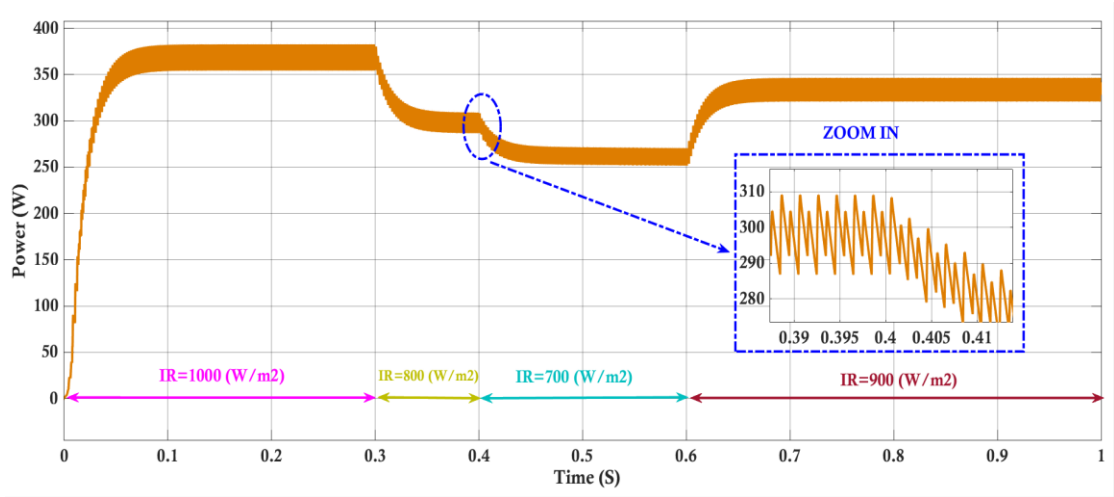


Figure 68: Power Simulation Result

Figure 69 presents the simulated voltage response of the ANN-based MPPT system under varying solar irradiance levels. The output voltage quickly reaches a steady state near 330 V and adjusts according to irradiance variations. As the irradiance decreases, the voltage correspondingly drops before stabilizing at a new operating point. The zoomed-in section highlights small transient oscillations during

the transition period, demonstrating the controller's capability to maintain stable operation under dynamic conditions.

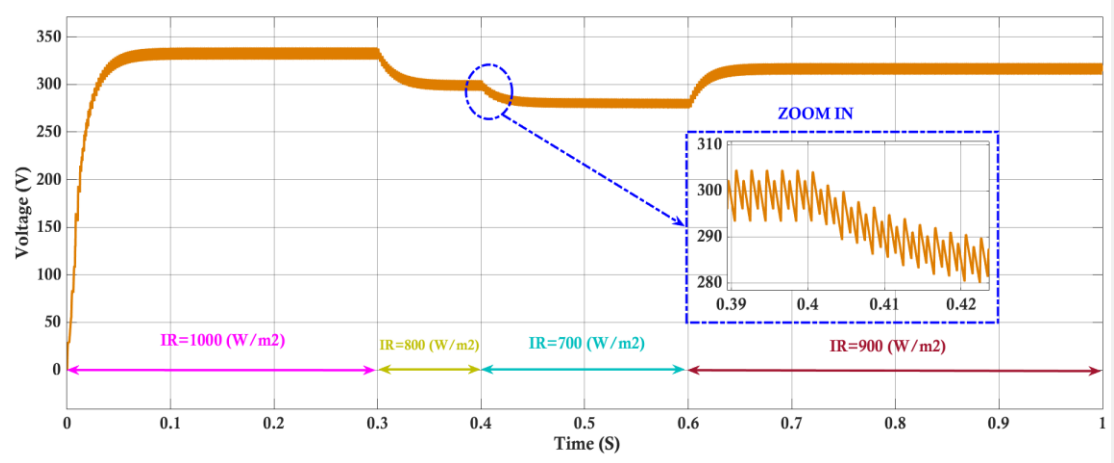


Figure 69: Voltage Simulation Result

Figure 70 illustrates the current response of the ANN-based Maximum Power Point Tracking (MPPT) system under varying solar irradiance conditions. The current initially stabilizes around approximately 1.1 A and then gradually decreases as the solar irradiance decreases. The zoomed-in view also shows slight transient oscillations during irradiance changes, reflecting the system's ability to adapt to dynamic conditions.

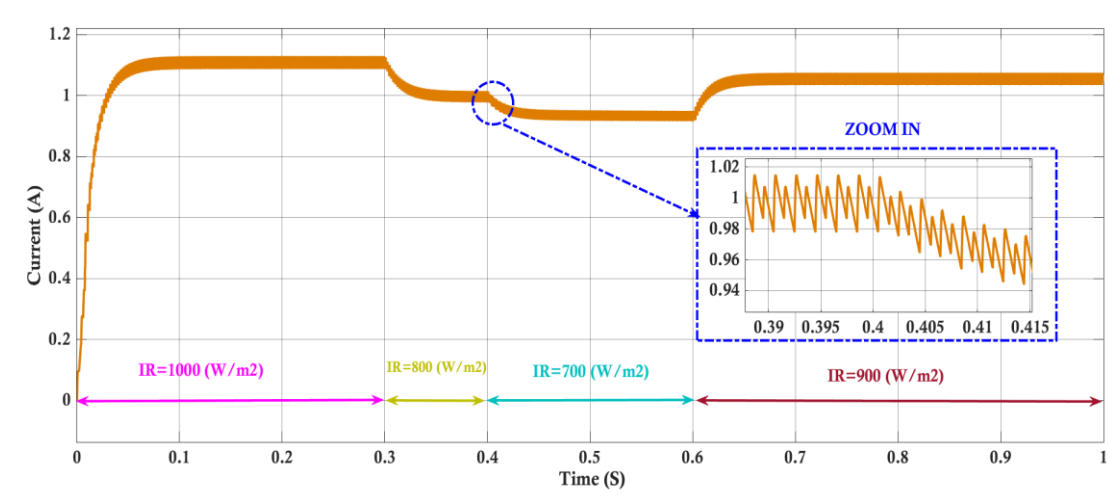


Figure 70: Current Simulation Result

3-4- Fuzzy Logic Controller (FLC) algorithm

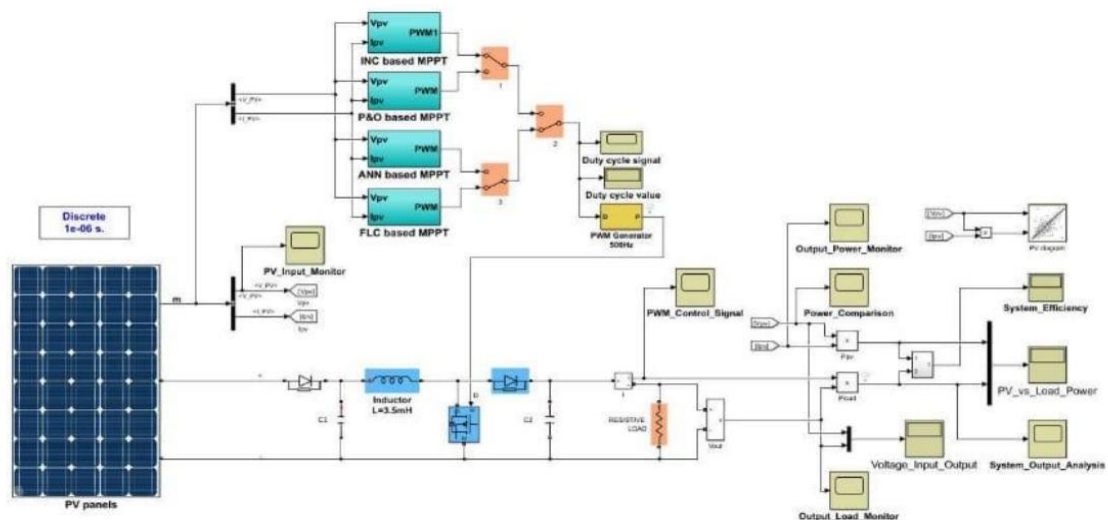


Figure 71: Schematic simulation system with FLC

3-4-1- Constant irradiance (1000 W/m²) and constant temperature (25°C)

The figure 72 shows the power response over time under constant irradiance using a Fuzzy Logic Controller (FLC). The output power rapidly increases during the transient stage until it reaches about 370 W, then stabilizes around this value with small oscillations in steady state. The zoomed view highlights these minor fluctuations, indicating continuous control adjustments to maintain the power near its maximum value.

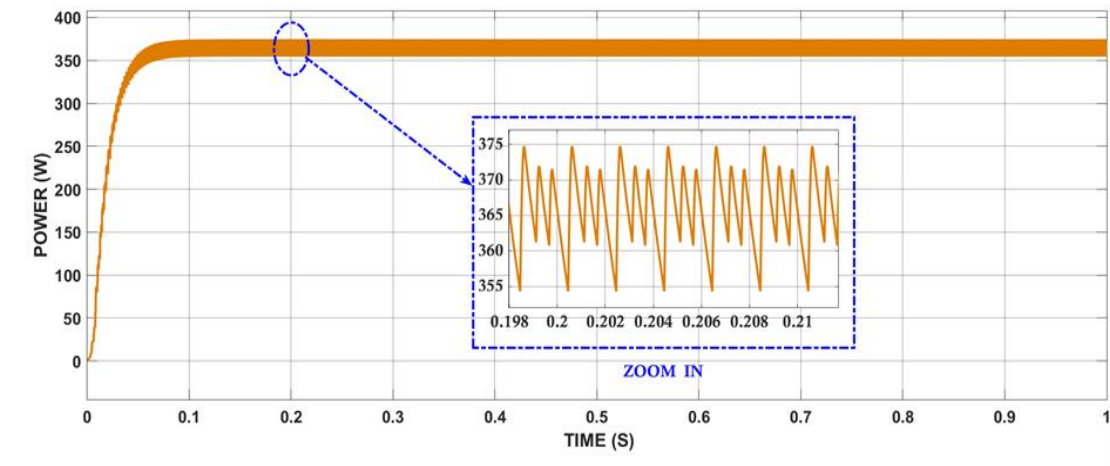


Figure 72: Power simulation result versus time for FLC in constant irradiance

The figure 73 illustrates the voltage response of the system over time under constant irradiance conditions. The voltage rises rapidly during the transient phase until it reaches approximately 330 V, indicating a fast dynamic response of the control system. After this initial rise, the voltage stabilizes around this value during the steady-state operation. The zoomed-in view highlights small oscillations around the operating point, which reflect the continuous control adjustments and the inherent dynamics of the system while maintaining operation near the maximum power point.

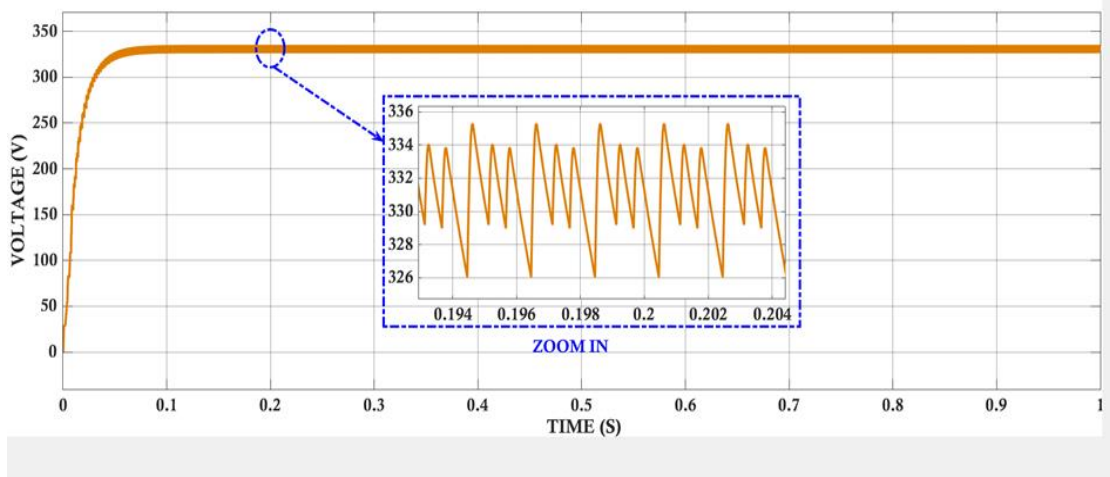


Figure 73: Voltage simulation result versus FLC in constan irradiance

Figure 74 illustrates the current response over time for the MPPT system based on a Fuzzy Logic Controller (FLC) under varying solar irradiance conditions. Initially, at an irradiance of 800 W/m^2 , the current rapidly increases and stabilizes around 1 A . At $t = 0.3 \text{ s}$, the irradiance rises to 1000 W/m^2 , causing the current to increase and stabilize near 1.1 A . Later, at $t = 0.6 \text{ s}$, the irradiance decreases to 600 W/m^2 , leading to a reduction in current to a new

steady value of about 0.85\,A. The zoomed-in section also shows small oscillations around the steady-state point, reflecting minor fluctuations due to the rule-based nature of the FLC while maintaining overall system stability.

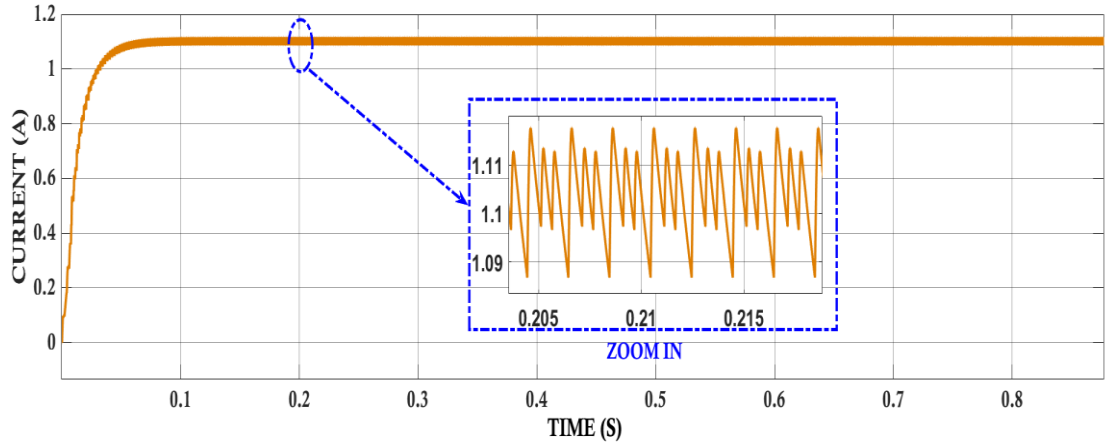


Figure 74: Current simulation result versus time for ANN in constant irradiance

3-4-2-Variable irradiances (1000, 800, 700, 900 W/m²) and constant temperature (25°C)

Figure 75 shows the power response of the FLC-based MPPT system under varying solar irradiance. Initially, at 1000\,W/m², the power quickly rises and stabilizes around 370\,W. As the irradiance decreases to 800\,W/m² and 700\,W/m², the power correspondingly drops to lower steady levels. When the irradiance increases again to 900\,W/m², the power rises and reaches a new stable value. The zoomed-in section also reveals small oscillations around the operating point during transitions, reflecting the controller's tracking process while maintaining overall system stability.

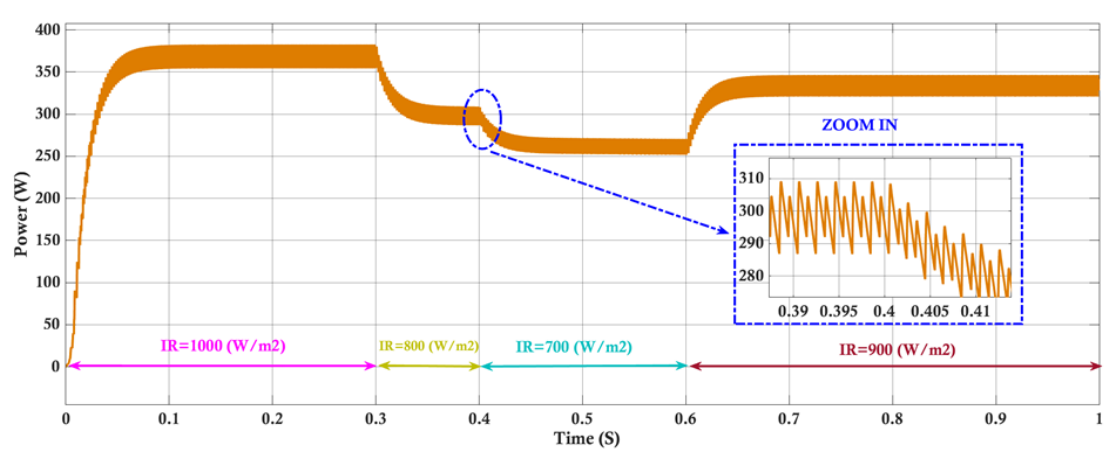


Figure 75: Power simulation result versus time for FLC in variable irradiances

Figure 76 shows the voltage response versus time of the FLC-based MPPT system under varying solar irradiance conditions. Initially, the voltage stabilizes around 330V at 1000W/m². As the irradiance decreases to 800W/m² and 700W/m², the voltage correspondingly drops to lower levels. When the irradiance increases again to 900W/m², the voltage rises and reaches a new steady state. The zoomed-in view also reveals small oscillations around the stabilization point, indicating the controller's dynamic response while maintaining overall system stability.

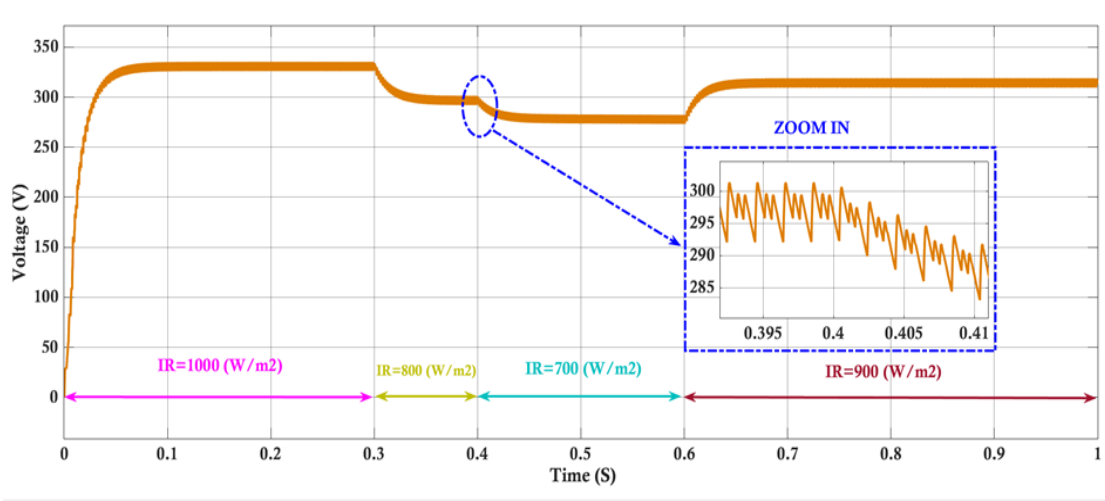


Figure 76: Voltage simulation result versus time for FLC in variable irradiances

Figure 77 illustrates the current response versus time for the FLC-based MPPT system under variable irradiance conditions. At the beginning, with an irradiance of 1000W/m², the current quickly rises and stabilizes around 1.1A, indicating a fast dynamic response. When the irradiance decreases to 800W/m² and then to 700W/m², the current correspondingly drops and stabilizes at lower levels. Later, when the irradiance increases to 900W/m², the current rises again and reaches a new steady-state value. The zoomed-in section highlights small oscillations around the operating point, which are minor fluctuations resulting from the control action of the fuzzy logic controller while maintaining overall system stability and effective tracking of the maximum power point.

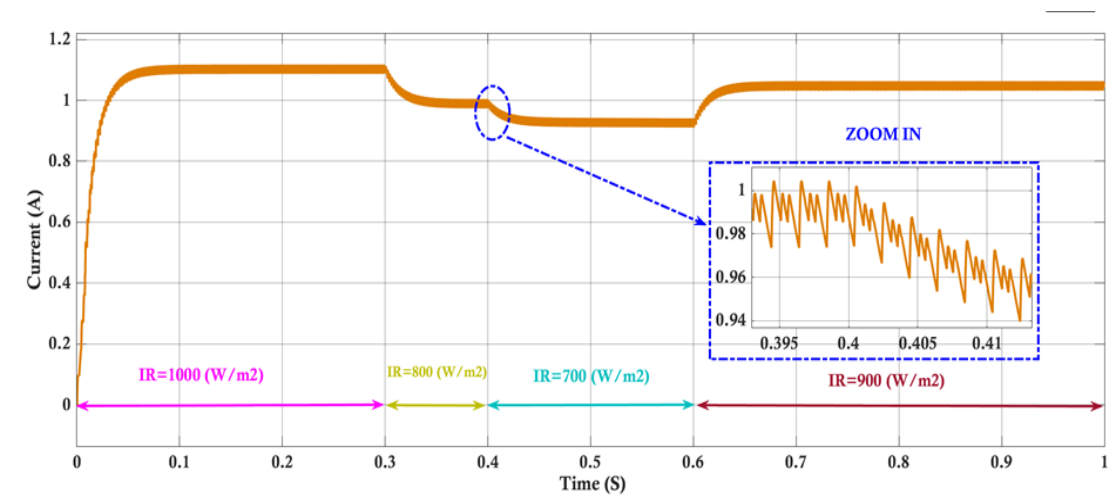


Figure 77: Current simulation result versus time for FLC in variable irradiances

4- Comparison and Analysis Between (P&O, INC, ANN) :

4-1- Constant Irradiance (1000 W/m²) :

The following figures compare the current and voltage outputs of three MPPT algorithms: Incremental Conductance (INC), Perturb and Observe (P&O), and Artificial Neural Network (ANN).

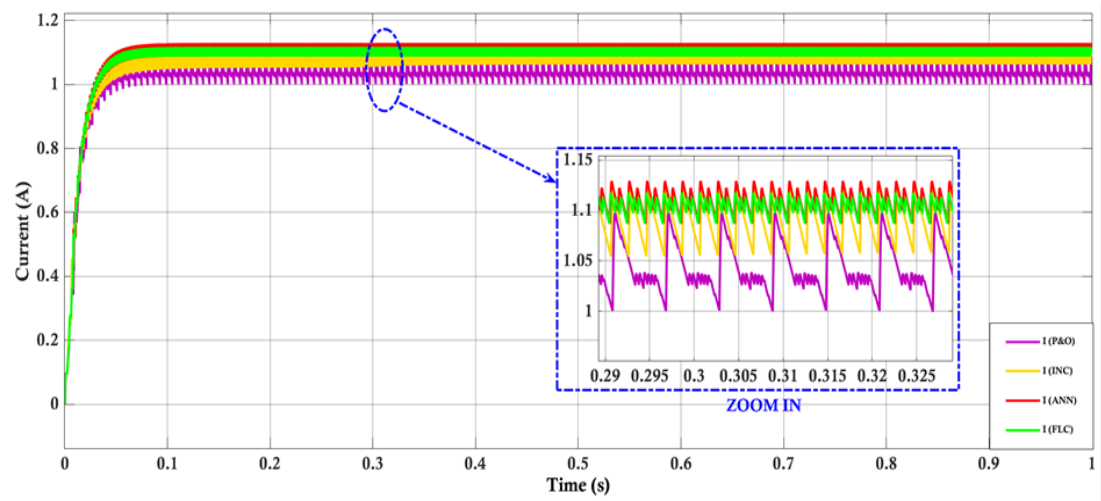


Figure 78: Current Simulation Result

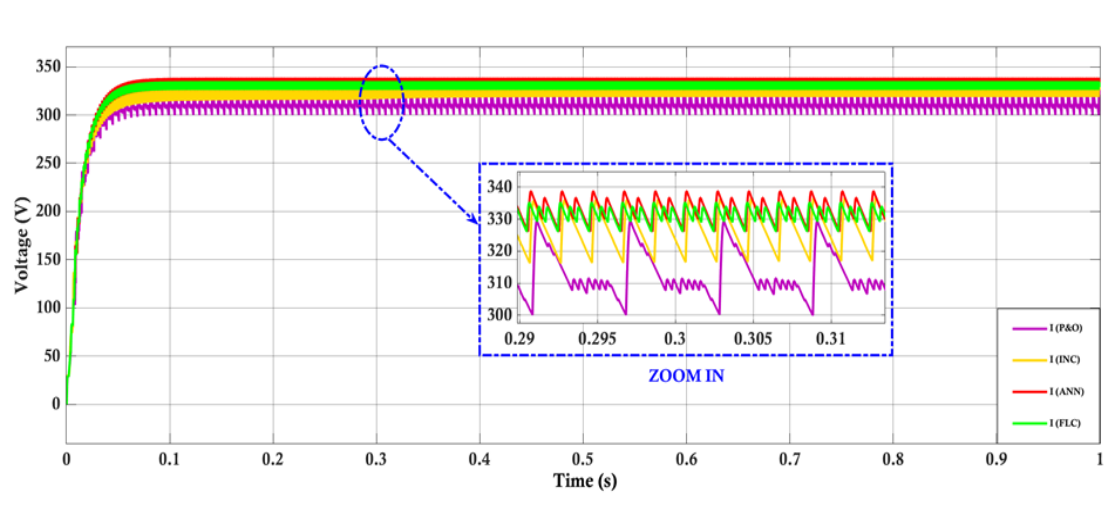


Figure 79: Voltage Simulation Result

4.1.2. Comparison:

- **Incremental Conductance (INC):** Shows fast stabilization in current and voltage with very small oscillations, indicating stable and efficient tracking.

- **Perturb and Observe (P&O):** Achieves rapid response but exhibits larger oscillations around the steady-state compared to the other methods.
- **Artificial Neural Network (ANN):** Provides fast convergence with minimal fluctuations, similar to INC, ensuring stable and efficient performance.

4.1.2. Analysis:

- **Best Performance:** Both INC and ANN algorithms demonstrate better performance with minimal oscillations in current and voltage, indicating higher stability and more accurate tracking of the maximum power point compared to P&O.
- **Slight Advantage:** The ANN algorithm may present a slight advantage over INC due to its adaptive learning capability, which allows improved optimization under different operating conditions.

Therefore, based on the presented simulation results, the Artificial Neural Network (ANN) appears to provide the most effective MPPT performance with stable operation and reduced fluctuations, followed closely by the Incremental Conductance (INC) method.

4-2- Variable Irradiances (1000, 800,700, 900 W/m²) :

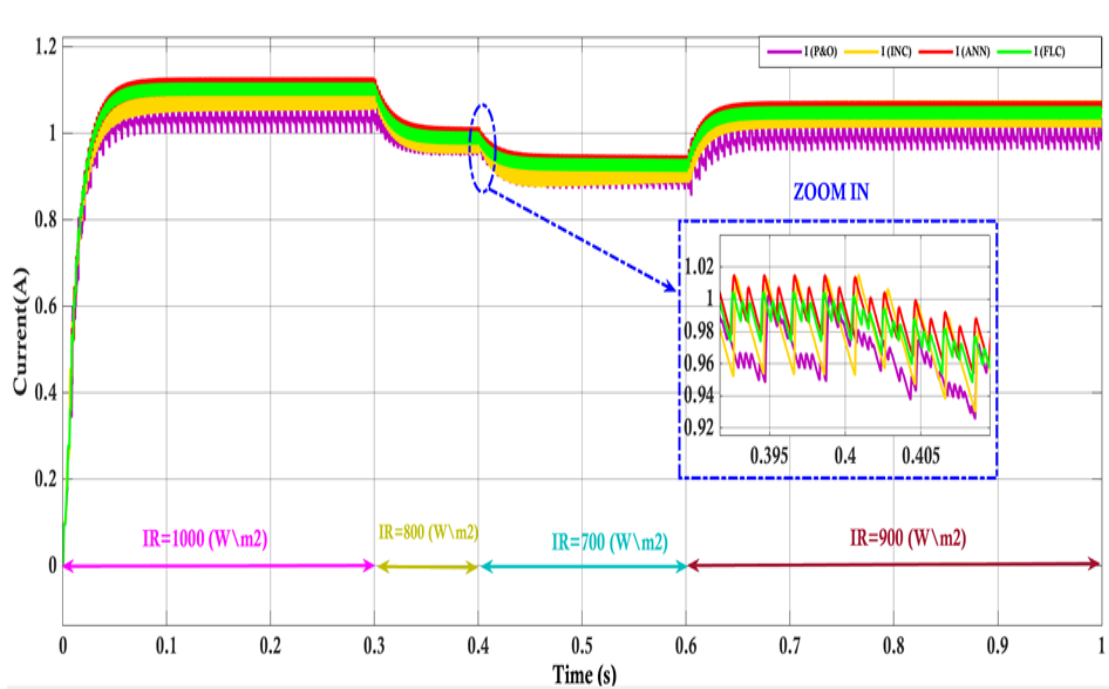


Figure 80: Current Simulation Result

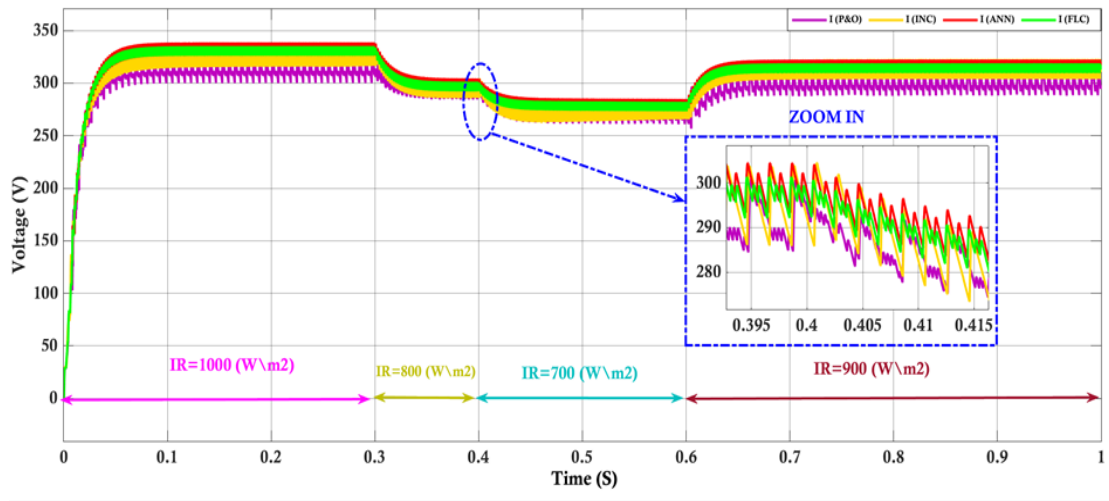


Figure 81: Voltage Simulation Result

4.1.2. Comparison :

- **Incremental Conductance (INC):** This algorithm provides relatively fast tracking of the maximum power point under changing irradiance conditions, but it exhibits moderate oscillations during transitions.
- **Perturb and Observe (P&O):** The P&O method shows larger oscillations around the operating point, which leads to lower stability during irradiance variations.
- **Artificial Neural Network (ANN):** The ANN approach demonstrates the best performance with minimal oscillations and smoother transitions, ensuring higher stability and tracking efficiency.

4.1.1. Analysis :

- **Best Performance :** The Artificial Neural Network (ANN) algorithm exhibits the highest level of performance, characterized by minimal oscillations and smooth transitions under varying irradiance conditions. This behavior reflects its strong stability and high efficiency in tracking the maximum power point..
- **Slight Edge :** Compared with the Incremental Conductance (INC) and Perturb and Observe (P&O) algorithms, the ANN approach demonstrates a noticeable advantage due to its adaptive learning capability and enhanced optimization performance in dynamic operating environments.

Based on the obtained results, the Artificial Neural Network (ANN) algorithm emerges as the most suitable MPPT technique, providing superior stability, accuracy, and efficiency when operating under fluctuating irradiance conditions.

5- Comparison of efficiency between algorithms (P&O, INC, ANN,FLC) :

5-1- Constant Irradiance (1000 W/m²) :

Table 4: Table of Efficiency

Algorithm	Efficiency
Perturb and Observe (P&O)	94.72%
Incremental Conductance (INC)	95.58%
Artificial Neural Network (ANN)	96.63%
Fuzzy Logic Controller (FLC)	92.81%

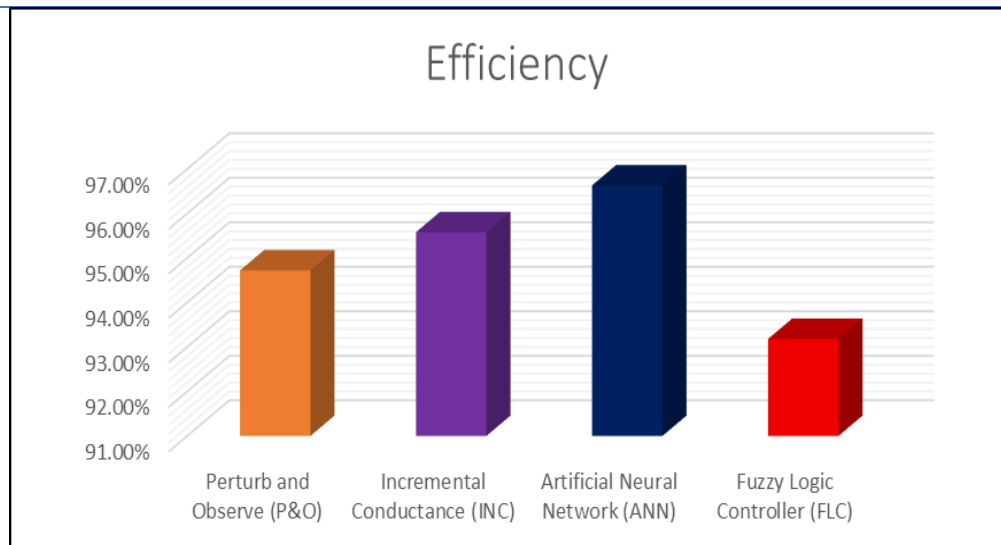


Figure 82: Chart of Efficiency

Under a constant irradiance of 1000 W/m², the efficiency comparison shows that the This figure illustrates the efficiency performance of different Maximum Power Point Tracking (MPPT) algorithms under a constant solar irradiance level of 1000 W/m². The results demonstrate that the Artificial Neural Network (ANN) based approach achieves the highest efficiency, reaching approximately 96.63%, which reflects its superior capability in accurately tracking the maximum power point. The Incremental Conductance (INC) algorithm follows with a slightly lower efficiency of about 95.58%, indicating reliable but comparatively less optimal performance. The Perturb and Observe (P&O) method records an efficiency close to 94.72%, while the Fuzzy Logic Controller (FLC) exhibits the lowest efficiency among the evaluated techniques. Overall, the comparison highlights the effectiveness of intelligent algorithms, particularly ANN, in enhancing photovoltaic system performance and maximizing energy extraction under stable irradiance conditions.

5-2- Variable Irradiances (1000, 800, 700, 900 W/m²) :

Table 5: Table of Efficiency

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%

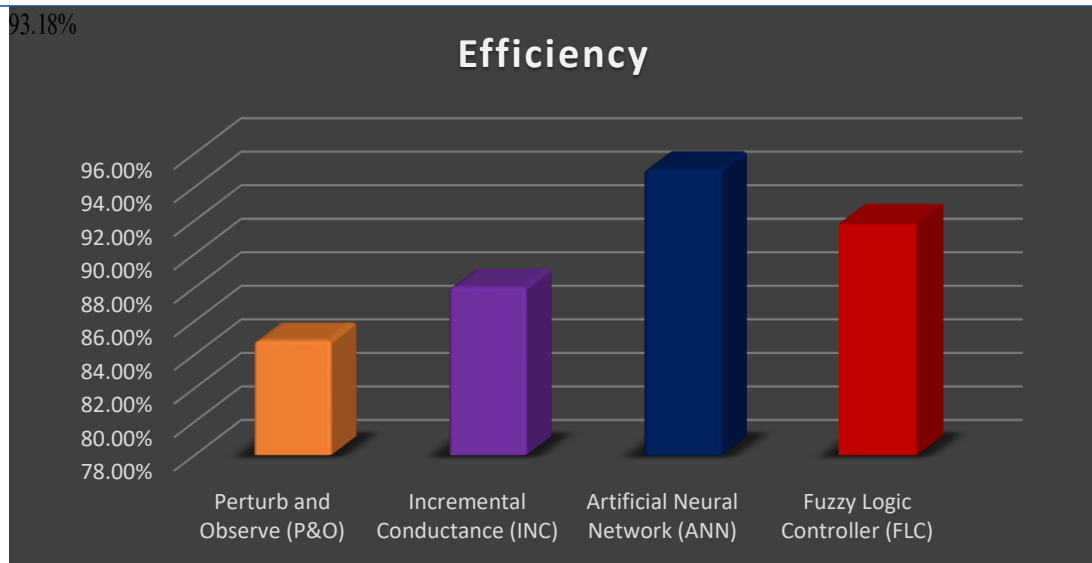


Figure 83: Chart of Efficiency

This figure presents the efficiency performance of different Maximum Power Point Tracking (MPPT) techniques under variable solar irradiance conditions. The results indicate that the Artificial Neural Network (ANN) algorithm achieves the best performance with an efficiency of approximately 95.06%, highlighting its strong capability to adapt to rapid variations in solar irradiance. The Fuzzy Logic Controller (FLC) follows with a relatively high efficiency of about 93.18%, demonstrating good adaptability in dynamic environments. Meanwhile, the Incremental Conductance (INC) method records an efficiency of nearly 88.04%, reflecting moderate tracking accuracy under changing conditions. In contrast, the Perturb and Observe (P&O) technique exhibits the lowest efficiency, around 84.84%, due to its higher sensitivity to fluctuations in irradiance.

Overall, these results emphasize the effectiveness of intelligent MPPT approaches, particularly the ANN-based method, in maintaining higher energy conversion efficiency and improving the stability of photovoltaic systems under dynamically changing environmental conditions.

6- Conclusion:

The performance of four Maximum Power Point Tracking algorithms, Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), Incremental Conductance (INC), and Perturb and Observe (P&O), is compared under constant and variable irradiation conditions in this research. The result indicates that ANN has highest efficiency always, 96.63% under constant irradiation and 95.06% under variable irradiation, due to its improved adaptability and predictability feature. INC is a tolerable second best, with the best performance (95.58% steady-state, 88.04% transient) but mean computational complexity. FLC and P&O are below optimal, particularly under dynamic conditions, and P&O experiences considerable reductions owing to oscillations and lower response times. FLC is superior to P&O under changing illumination but is less stable and efficient than ANN and INC. Thus, ANN suits maximum efficiency for varying environments, whereas P&O and INC suit easier or cost-cutting systems. The above finding comes to serve as a pointer towards the need for selecting an algorithm for environment stability and system need.

Conclusion générale

Conclusion générale

This study provided a comprehensive overview of photovoltaic energy conversion systems, beginning with the fundamental principles of solar radiation and the photovoltaic effect that enables solar cells to convert sunlight into electrical energy, while examining the modeling and electrical characteristics of photovoltaic generators and highlighting the different types of photovoltaic cells based on silicon crystalline structures, as well as the various factors influencing their performance and efficiency. The study also emphasized the essential role of DC–DC converters in photovoltaic power management systems, where different converter topologies such as buck, boost, and buck–boost enable efficient voltage regulation and energy transfer, making them indispensable in modern energy applications. Furthermore, particular attention was devoted to Maximum Power Point Tracking (MPPT) techniques, which play a crucial role in maximizing the energy extracted from photovoltaic panels by continuously adjusting the operating point of the system under varying environmental conditions such as solar irradiance and temperature changes. Several MPPT algorithms were therefore analyzed and compared in terms of performance, stability, and efficiency, revealing that although conventional methods such as Perturb and Observe and Incremental Conductance provide acceptable tracking performance, their effectiveness remains limited under rapidly changing conditions. In contrast, the Artificial Neural Network (ANN) based MPPT approach demonstrated superior efficiency due to its adaptive learning capability, high tracking accuracy, and strong dynamic response, allowing the photovoltaic system to maintain optimal operation and achieve improved energy harvesting performance. Consequently, the ANN algorithm emerges as the most effective and reliable solution among the studied methods for optimizing photovoltaic system output and ensuring long-term operational stability, thereby supporting the development of intelligent and sustainable renewable energy technologies.

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