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Performance Improvement of Solar PV Systems Using Various MPPT Algorithms (P&O, FLC, INC and ANN)

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Thank you ...

DEDICATION

To my mother and father , my first and greatest teachers.
To my sister who told me I could.

To my professors, for their guidance and wisdom .

To knowledge itself , the only treasure that grows when
shared. I dedicate this humble work, hoping it is the beginning,
not the end.

Alem Smati Abdelaziz

DEDICATION

To my parents, the reason I am where I am today. Thank
you for your patience and for always believing in me through the
long nights and the hard work. To my family and friends, thanks
for being there when I needed it most. This one is for you

Bedra Yacine

DEDICATION

All praise is due to Allah, by whose grace this work has been
accomplished.

With great pride and gratitude, I dedicate this work:

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

To my dear family, who have always been my strength and
inspiration.

Belkacem Louai Mohammed Yazid

Résumé:

Le travail intitulé « Amélioration des Performances des Systèmes Solaires PV en Utilisant Divers Algorithmes MPPT (P&O, FLC, INC et ANN) » propose une stratégie de commande hybride visant à améliorer l'efficacité et la stabilité des systèmes photovoltaïques. En combinant les méthodes Perturb and Observe (P&O), Conductance Incrémentale (INC), Commande par Logique Floue (FLC) et Réseau de Neurones Artificiels (ANN), le système s'adapte aux variations d'irradiance et de température de manière plus efficace que les algorithmes classiques utilisés individuellement.

Les simulations montrent que l'approche intégrée permet une convergence plus rapide, des oscillations minimales et une efficacité de suivi plus élevée ($\approx 99\%$) dans des conditions d'ensoleillement uniformes et partiellement ombragées. Le contrôleur MPPT hybride tire parti de la simplicité des algorithmes P&O et INC, combinée à l'intelligence adaptative de la FLC et du RNA, garantissant ainsi une extraction de puissance robuste et optimale.

Dans l'ensemble, cette étude démontre que l'intégration multi-algorithmes améliore significativement les performances, la fiabilité et le rendement énergétique des systèmes photovoltaïques, ce qui les rend particulièrement adaptés aux applications solaires intelligentes modernes.

Mots-clés:

Conversion d'énergie – Modélisation – Optimisation – MPPT.

Abstract:

The work “Performance Improvement of Solar PV Systems Using Various MPPT Algorithms (P&O, FLC, INC and ANN)” proposes a hybrid control strategy to enhance the efficiency and stability of photovoltaic systems. By combining Perturb and Observe (P&O), Incremental Conductance (INC), Fuzzy Logic Control (FLC), and Artificial Neural Network (ANN) methods, the system adapts to changing irradiance and temperature more effectively than conventional single algorithms. Simulations show that the integrated approach achieves faster convergence, minimal oscillations, and higher tracking efficiency ($\approx 99\%$) under both uniform and partial shading conditions. The hybrid MPPT controller leverages the simplicity of P&O and INC with the adaptive intelligence of FLC and ANN, ensuring robust and optimal power extraction. Overall, the study demonstrates that multi-algorithm integration significantly improves PV system performance, reliability, and energy yield, making it well-suited for modern smart solar applications.

Keywords:

Energy conversion – Modeling – Optimization – MPPT.

الملخص

يقترح العمل المعنون بـ « تحسين أداء أنظمة الطاقة الشمسية الكهروضوئية باستخدام خوارزميات متعددة لتتبع نقطة القدرة العظمى P&O، FLC، INC، و ANN استراتيجية تحكم هجينة تهدف إلى تعزيز كفاءة واستقرار الأنظمة الكهروضوئية. من خلال الجمع بين طرق الإزعاج والمراقبة (P&O)، والتوصيلية التزايدية (INC)، والتحكم بالمنطق الضبابي (FLC)، وشبكات الأعصاب الاصطناعية (ANN)، يتكيف النظام مع تغيرات الإشعاع الشمسي ودرجة الحرارة بشكل أكثر فعالية مقارنةً بالخوارزميات الفردية التقليدية. تُظهر نتائج المحاكاة أن النهج المتكامل يحقق تقارباً أسرع، وتذبذبات أدنى، وكفاءة تتبع أعلى (≈99%) في ظروف الإشعاع الموحد والظل الجزئي على حد سواء. يستفيد وحدة التحكم MPPT الهجينة من بساطة خوارزميتي P&O و INC مع الذكاء التكيفي لـ FLC و ANN، مما يضمن استخراجاً مثالياً وموثوقاً للطاقة. وبشكل عام، تُثبت هذه الدراسة أن دمج الخوارزميات المتعددة يُحسن بشكل ملحوظ من أداء وموثوقية وإنتاجية أنظمة الطاقة الشمسية الكهروضوئية، مما يجعلها مناسبة تماماً للتطبيقات الشمسية الذكية الحديثة.

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

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General Introduction

General introduction

General Introduction:

Distinguished members of the examination committee, respected supervisors, and honorable attendees, it is my great pleasure to present today the results of my Master's thesis entitled "Performance Improvement of Solar PV Systems via Multi-Algorithm MPPT Integration."

In recent decades, the global energy sector has undergone profound transformations driven by the continuously increasing demand for energy and the growing environmental concerns associated with conventional energy sources. These challenges have encouraged researchers and engineers to intensify their efforts toward developing advanced energy conversion systems capable of improving efficiency and ensuring the optimal utilization of available energy resources.

Within this context, solar-to-electrical energy conversion systems play a fundamental role in a wide range of modern technological applications, particularly in renewable energy systems and electromechanical power generation technologies. However, the effectiveness of such systems does not rely solely on their physical configuration; it also depends significantly on the accuracy of their mathematical modeling and on the control strategies implemented to enhance their operational performance.

Among the various approaches proposed in the literature, the Maximum Power Point Tracking (MPPT) strategy has emerged as one of the most effective techniques for maximizing energy extraction. This method aims to operate the system at its optimal operating point, where the maximum available power can be harvested, even under varying operating conditions.

Based on this scientific background, the present work focuses on the modeling and optimization of a photovoltaic (PV) energy conversion system under an MPPT strategy. The main objective of this study is to analyze the dynamic behavior of the proposed system, develop an appropriate mathematical model describing its physical characteristics, and evaluate the effectiveness of the adopted control strategy in maximizing the extracted power and improving the overall system efficiency.

Chapter I

Fundamentals of Solar

Photovoltaic Energy

I.1 Introduction :

Solar energy, which is the most plentiful energy we have on Earth, is what keeps photovoltaic (PV) systems going. PV energy, often called solar energy, is the energy captured by PV cells that turn sunlight right into electricity. In this part, we will discuss about solar energy in general. We'll go over the basics of how PV systems work and how they make electricity using the photovoltaic effect. Plus, we'll talk about how solar energy changes based on where you are and what time of year it is.

I.2 Overview and Motivation

The increasing global demand for electrical energy, predominantly derived from fossil fuels such as oil and coal, has placed considerable pressure on fossil fuel reserves and has significantly impacted the global environment. The limited supply of fossil fuels, which remain the predominant energy source, results in substantial greenhouse gas emissions, including nitrous oxide (N_2O), carbon dioxide (CO_2), and methane (CH_4), that are key contributors to climate change (IPCC, 2007).

Furthermore, the use of fossil fuels for transportation and the ongoing expansion of industrial activities have led to severe air pollution, compounding environmental challenges [1, 2]. To sustain economic growth while safeguarding natural ecosystems for future generations, it is imperative to transition to alternative, sustainable, and clean energy sources. Achieving these goals necessitates coordinated global efforts, as emphasized in international frameworks like the Kyoto Protocol[3].

In response to these challenges, renewable energy sources (RES) have been increasingly promoted as an alternative for power generation. Over the past few decades, the contribution of renewable energy to electricity grids has grown substantially due to policy measures aimed at combating climate change and ensuring a sustainable energy supply (World Energy Outlook). In 2023, RES accounted for over 33% of the global power generation capacity, as illustrated in Figure 1.1, demonstrating their rising significance in the energy mix [4]. Unlike fossil fuels, renewable energy sources such as wind, solar, biomass, and hydroelectric power produce energy without emitting greenhouse gases, thereby contributing to the mitigation of climate change and a reduction in air pollution.

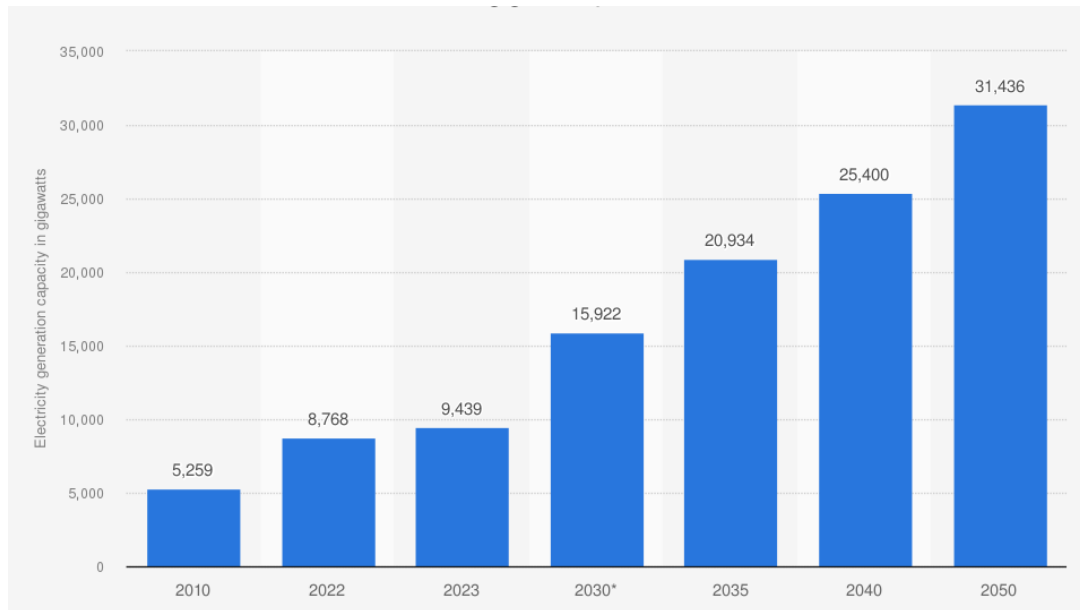


Figure (I. 1): Global power generating capacity

Among renewable energy technologies, solar photovoltaic energy and wind power have experienced substantial growth, outpacing other forms of RES. As shown in Figure 1.2, photovoltaic systems (PV) and wind power constitute approximately 33% and 28% of new renewable energy installations, respectively. This trend underscores the potential of these technologies to play a leading role in decarbonizing the energy sector. The geographical potential for solar energy, in particular, varies significantly by region, as illustrated in Figure 1.3.

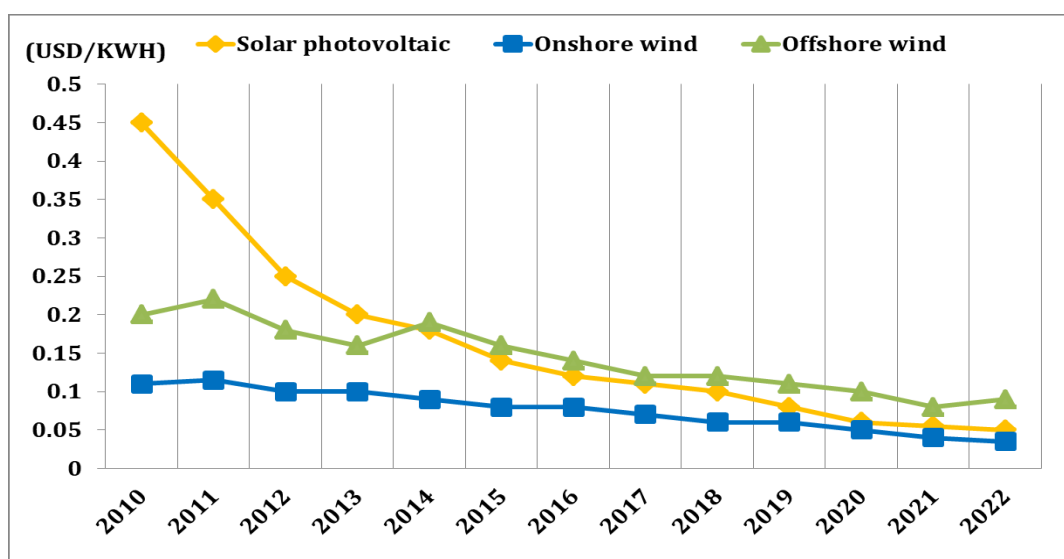


Figure (I. 1): Levelised cost of electricity from newly commissioned solar PV, onshore wind power and offshore wind power, 2010-2022

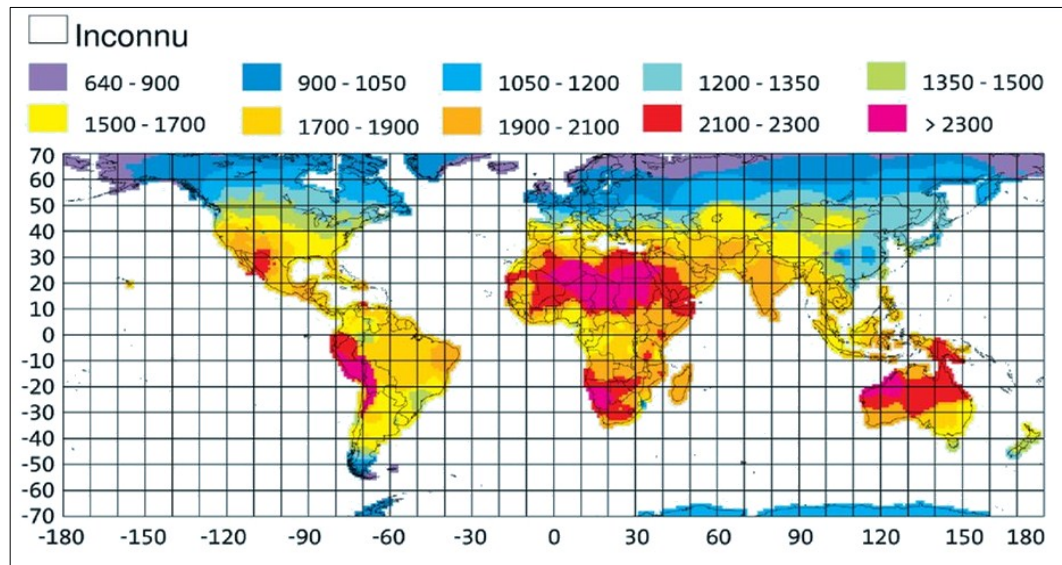


figure (I. 2): Solar irradiation map of the world from photovoltaic guider

The levelized cost of electricity (LCOE) associated with renewable energy technologies has experienced a substantial decline in recent years. Among these, onshore wind energy has exhibited the most pronounced reduction, with the global average LCOE decreasing by 50% between 2010 and 2022 to reach USD 0.033 per kilowatt-hour (kWh). Similarly, solar photovoltaic (PV) systems have observed a significant cost reduction, with the global average LCOE recorded at USD 0.049 per kWh in 2022. In contrast, offshore wind energy remains comparatively more expensive, with an LCOE of USD 0.081 per kWh (refer to Figure 1.2).

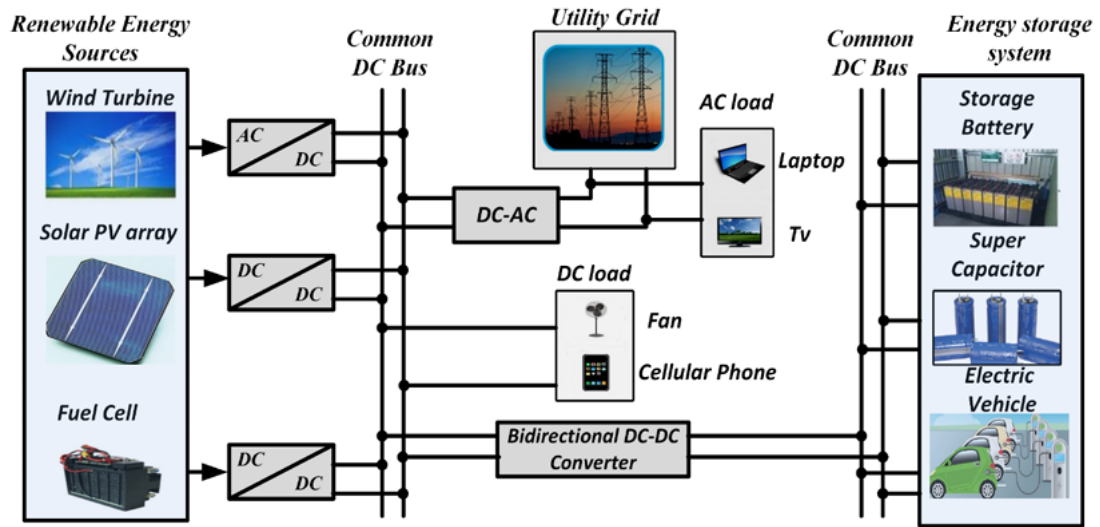
Despite these advancements in cost-efficiency, the integration of renewable energy sources, particularly solar PV, into the power grid presents notable challenges due to their intermittent nature. The direct current (DC) voltage output from these systems is inherently variable, influenced by fluctuating environmental conditions, which renders direct grid connection impractical. This challenge has catalyzed advancements in power electronic converters (PECs) as a pivotal technological solution.

Power electronic converters serve as intermediary devices between renewable energy systems and the electrical grid. These converters address the variability of output voltage by dynamically regulating it, ensuring efficient power conversion, and maintaining a balanced power distribution. Through these functions, PECs enhance grid compatibility and ensure the reliable delivery of power generated from renewable sources.

I.3 Power Electronics Converters for Renewable Energy System

Power electronic converters (PECs) are essential in facilitating the integration of renewable energy sources (RES) with the electrical grid or load systems. Their operation critically impacts the overall performance of the system, particularly influencing aspects such as stability, reliability, efficiency, power quality, and the consumption ratio.

To ensure energy conversion processes that are both cost-effective and efficient, various innovative Photo electrochemical (PEC) systems are being developed alongside the increasing practical implementation of renewable energy technologies [4]. Figure 1.4 presents a detailed framework for the integration of Renewable Energy Sources (RES) through the application of Power Electronic Converters (PEC). The incorporation of RES into electrical systems necessitates the deployment of PEC to align the outputs of RES with the requirements of the power grid. Consequently, significant advancements have been made in enhancing the efficiency of PEC systems. These improvements can be achieved through two primary approaches: (a) the development of novel power converter designs or (b) the implementation of advanced control strategies.



Figure(I. 3): Schematic exhibiting the relationship of a RES to the electricity grid.

The classification of converters in renewable energy systems (RES) encompasses two primary categories: galvanic ally isolated and non-isolated variants [6], [7]. Galvanically isolated converters, also known as transformer-based converters, employ a transformer to achieve input-output isolation, as highlighted in the topological analyses of [8],[9], [10]. This isolation mechanism enhances their functional potential. However, the inclusion of transformers introduces notable challenges, including increased financial costs, larger

physical dimensions, and reduced operational efficiency. These limitations, absent in non-isolated or transformer-less solutions, are substantiated by empirical findings from case studies [11, 12]. Therefore, non-isolated converters emerge as a more favorable option in power conversion processes when all critical factors are considered.

I.3.1 Review of PV Energy System Applications

Photovoltaic (PV) energy conversion systems play a crucial role in the integration of renewable energy into the utility grid, providing a sustainable and efficient solution for electricity generation. Figure 1.5 illustrates the structural configuration of such a system, beginning with PV arrays that harvest solar irradiance and convert it into direct current (DC) electrical energy, which is subsequently stabilized via DC bus structures. A multilevel power electronics converter serves as the pivotal component, facilitating the conversion of DC power into alternating current (AC) power characterized by high quality and reduced Total Harmonic Distortion (THD). A filtering stage ensures compliance with grid standards by attenuating high-frequency noise, while an optional transformer is incorporated to perform voltage adaptation and provide electrical isolation between the PV system and the grid. The control unit, incorporating a Maximum Power Point Tracking (MPPT) controller, ensures optimal energy harvesting from the PV arrays and precise regulation of the power electronics converter. Ultimately, the AC power is injected into the utility grid, demonstrating a sophisticated integration of advanced control algorithms and power conversion technologies for efficient solar energy utilization and grid compatibility.

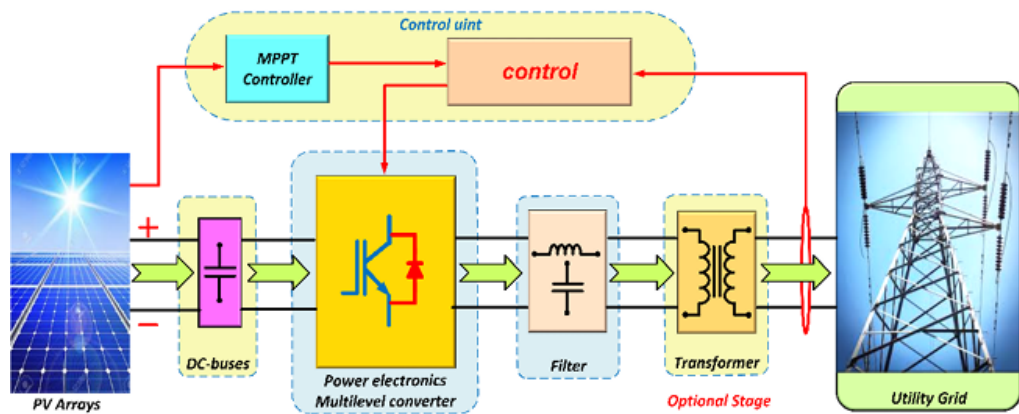


Figure (I. 4): photovoltaic (PV) system with power electronics and the needed control.

I.3.2 Classification of power converters

Power electronic converters have been used in many industrial applications for efficient power conversion and energy conservation. Depending on the type of electric power conversion and the electric power flow, the power converters can be divided into the following four categories:

- AC-DC rectifiers: Convert a single-phase or three-phase AC voltage to DC is used as front-end in variable-speed motor drives and wind energy conversion systems.
- DC-DC converters: Convert a DC voltage from one level and a certain polarity to a DC voltage of another level and in some applications to another polarity.
- DC-AC inverters: Conversion from DC to variable-voltage and variable-frequency AC is used invariable-speed motor drives. Conversion of unregulated or regulated DC to fixed AC is used in grid-connection of renewable energy sources.
- AC-AC cycloconverters: Convert an AC voltage of one level, frequency and number of phases to an AC voltage of a different level, frequency, and in some applications to different number of phases.

I.3.3 Classification of DC–DC converters

Many researchers have addressed different types of DC–DC converters for renewable energy applications and storage to improve and enhance efficiency whilst overcoming the weaknesses of converters. DC–DC converters are categorized into three major technologies based on their operation modes, as shown in Figure 2 [13-15]. They are linear mode, hard switching mode, and soft switching mode. The linear mode has features such as simplicity, low noise with good regulation, and quick response. On the other hand, its drawback is low efficiency due to power losses in various working conditions. Hard switching mode converters can be sub-categorized into non-isolated and isolated converters based on galvanic isolation. The buck, boost, buck–boost, and Cuk converters are typical examples of the hard switching mode topologies that are without galvanic isolation (non-isolated) and identified as chopper circuits. However, galvanic isolation (transformer) is necessary for safety causes when the converters are supplied by the utility grid. Power converters (PCs), with their control techniques, help regulate voltages of nodes in microgrid with different types of loads such as resistive, inductive, nonlinear, constant power, or critical loads. However, constant power loads (CPLs) affect the stability of the voltage in the output of PCs and are usually difficult to regulate with traditional control techniques [16, 17].

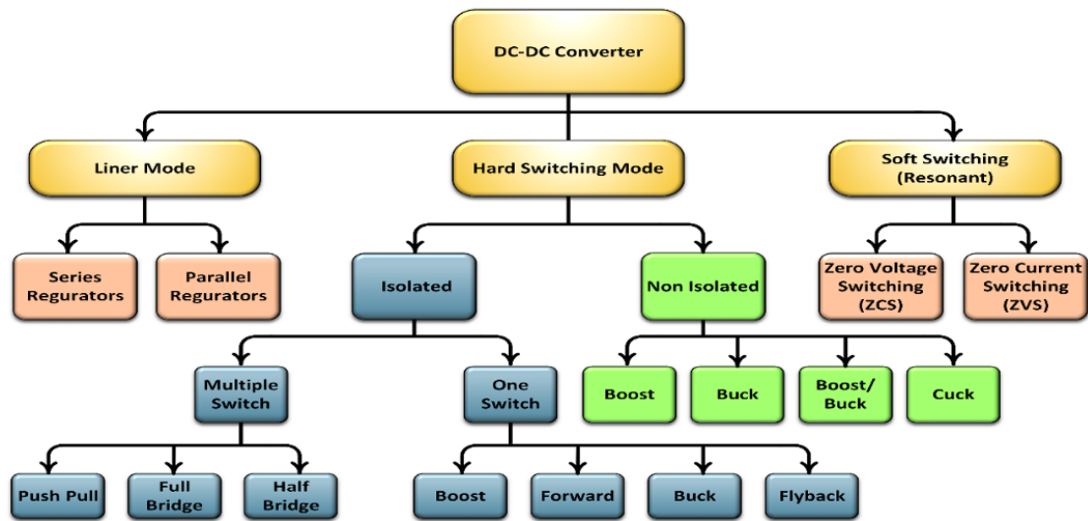


Figure (I. 5): . Classification of DC–DC converters [18]

Solar Radiation :

The Sun sends out all sorts of radiation. Besides super-fast, high-energy cosmic ray particles, it also sends out electromagnetic waves, everything from radio waves to gamma rays, including light we can see.

The way the Sun emits electromagnetic waves is pretty close to what you'd expect from a black body at 5800 Kelvin, going by Planck's law. The strongest emission is in the yellow part of the spectrum (at about 570 nm). The radiation is split pretty evenly between visible light and infrared, with just 1% in ultraviolet. When this radiation gets down to sea level, after going through the atmosphere, a lot of it gets filtered out. You can easily spot things like ozone absorption bands (ozone absorbs a lot of ultraviolet), plus oxygen, carbon dioxide, and water doing their thing.

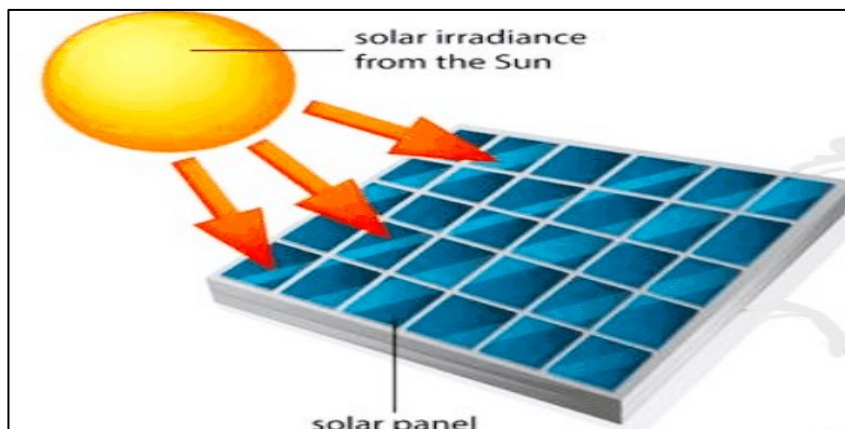
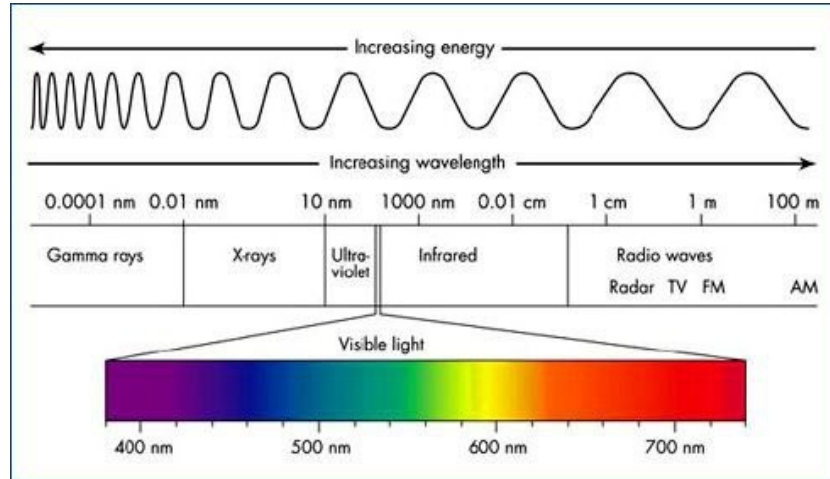


Figure (I. 6): Representation of Solar Radiation

Radiation Spectrum:

Solar energy can seem difficult, but it's really just the heat and light provided by the sun. Last century, we invented photovoltaic cells, which let us turn solar energy into power for the earth. Photovoltaic solar panels change light into electricity.

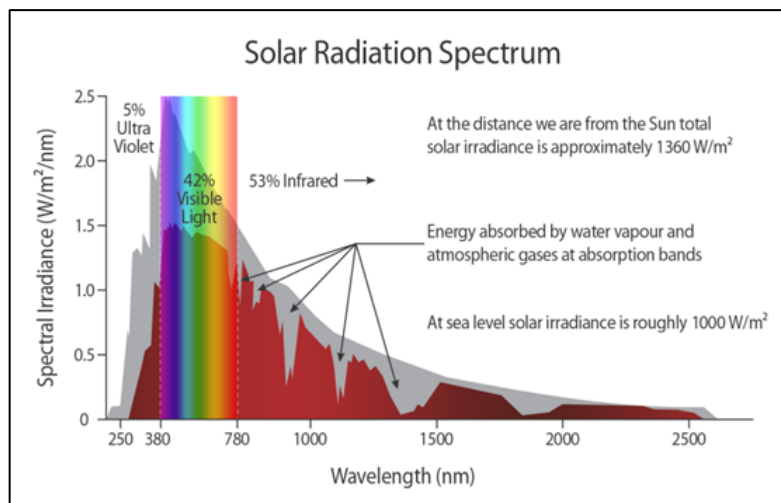


Figure(I. 7): Solar Radiation Spectrum

Although the electromagnetic spectrum is very broad, 99.8% of the Sun's EM radiation is radiated within 20 to 2500 nanometers which is a very narrow bandwidth.

Only a small fraction of solar radiation, ranging from radio waves with wavelengths of several decameters to the softest rays of ultraviolet light, reaches the surface of the Earth, since most is reflected or absorbed in the atmosphere and ionosphere [2].

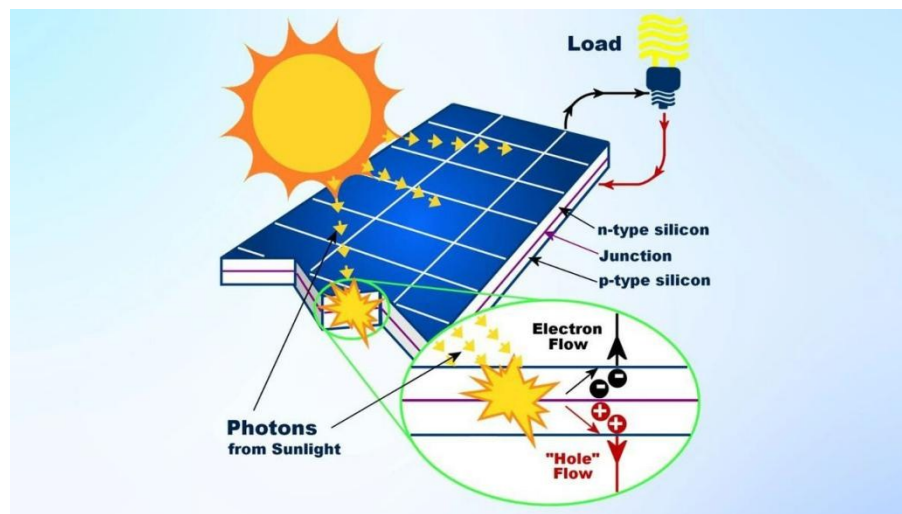
By analyzing figure (1.3), the solar spectrum, we can see that solar energy consists of 5% ultraviolet light, 42% visible light and 53% near infra-red light.



Figure(I. 8): Representation of Solar Radiation Spectrum

Conversion of Solar Radiation by PV Effect:

A PV cell consists of two polarized silicon layers. To do this, a number of boron atoms are added to the silicon to form the "P layer", which is positively charged. To create a negatively charged "N layer", a certain number of phosphorus atoms are introduced, creating a potential barrier. A photon with an energy greater than the band gap can be absorbed by the semiconductor, breaking a bond between two atoms in the valence band, releasing an electron and leaving a "hole" in its place. The potential difference between these holes and electrons is great enough that, if they are connected, the electrons will travel from one layer to the other to create an electric current [1].



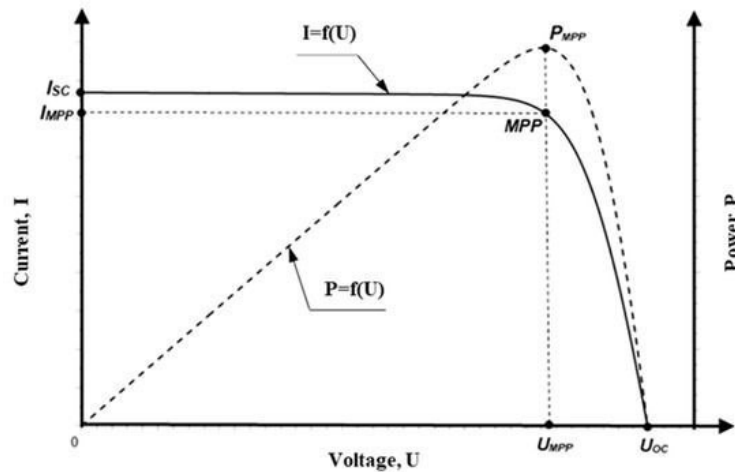
Figure(I. 9): Solar Radiation Conversion by PV Effect

Photovoltaic Generator:

Photovoltaic sensors are characterized by the relationship (or curve) between current and voltage, $I=f(V)$ as shown in figure 1.5.

This modeling is common in estimating the output of a sensor (voltage or current) based on two inputs, the temperature and the illumination received by the sensor.

The current delivered by a photovoltaic module at a given voltage depends only on the illumination and temperature of the cell. At constant temperature and illumination, the conversion efficiency of a cell depends on the load in the electrical circuit. In the open-circuit condition ($R_c = \infty$, $I = 0$, $V = V_{oc}$) or short circuit ($R_c = 0$, $I = I_{cc}$, $V = 0$) no energy is conveyed to the outside. There's a best load resistance value (R_{opt}) for a solar cell where it gives the most power (P_{max}) to the load. This happens when the power ($P = V_{max} \times I_{max}$) from the solar cell is at its highest.



Figure(I. 10): Typical Characteristics of a PV Generator

The efficiency is defined as $\eta = P/P_\gamma$ where P_γ is the power of incident light on the surface of the cell. The efficiency is maximum $\eta_{\max} = P_{\max}/P_\gamma$ at the optimal value R_{opt} of the load resistance R_c . R_{opt} is not a parameter of the cell, but depends on the spectrum of the incident radiation and on the junction temperature: the efficiency decreases when the temperature increases. For this reason, hybrid sensors were developed: they are composed of a thermal sensor integrated with a solar cell. These sensors allow hot water to be generated and help to increase the efficiency of the photovoltaic cell.

Solar cell power ($P = I \times V$) and how well it works depend on a few things: what it's made of (like amorphous, polycrystalline, or monocrystalline silicon), how it's put together (layer thickness, multilayers, etc.), and outside stuff (temperature, light, the power of the light, and the electrical circuit it's hooked up to).

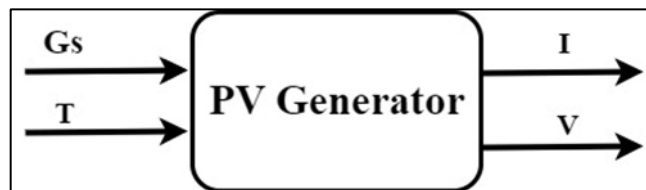


Figure (I. 11): Block Diagram of a PV Generator

Photovoltaic Cell:

Solar panels are made of solar cells linked together, sealed in resin, and sandwiched between two panes of tough glass (double-glass panels) or a glass pane and a Tedlar sheet (glass/Tedlar panel). Usually, this setup is put in an aluminum frame, but you can get frameless panels, too, for putting on roofs or walls using aluminum supports. How much

power a panel makes depends on its size and how much sunlight hits it. It's measured in peak watts (Wp), which is the panel's max power under ideal sunlight (1000 W/m^2). The voltage a panel puts out relies on how many cells are wired together in a chain. For smaller panels (under 75 Wp), the voltage is usually around 12 to 15 volts. If you want more powerful panels, you add more cells in a chain to raise the voltage, and you add extra chains of cells side-by-side to raise the current. The voltage can then be 24 volts or higher, depending on what you need to power. Panels come in different sizes, usually from 0.5 to 1 square meter, but some custom ones can be as big as 3 square meters. A bunch of panels linked together makes a larger panel system, and many of these systems together form a solar array. By wiring panels in series and/or side-by-side, you can get the voltage and power you need [1].

Modelling of a PV Cell:

The way a solar panel works can be explained using a simple model that's been around since Shockley's time. He figured out how a single solar cell works, and then people expanded his idea to entire solar panels by thinking of them as many identical cells linked together.

People who study solar cells usually talk about them as if they're a generator that sends out electricity, acting like a power source with a diode attached. To get a more realistic model, we add two resistances, called R_s and R_{sh} , to stand for things that happen inside the cell. You can see this in the circuit diagram in Figure (1.7).

The series resistance, R_s , is mostly from the stuff the cell is made of and the connections inside. Shunt resistance, R_{sh} , is there because some current leaks out at the junction, which depends on how the cell was made.

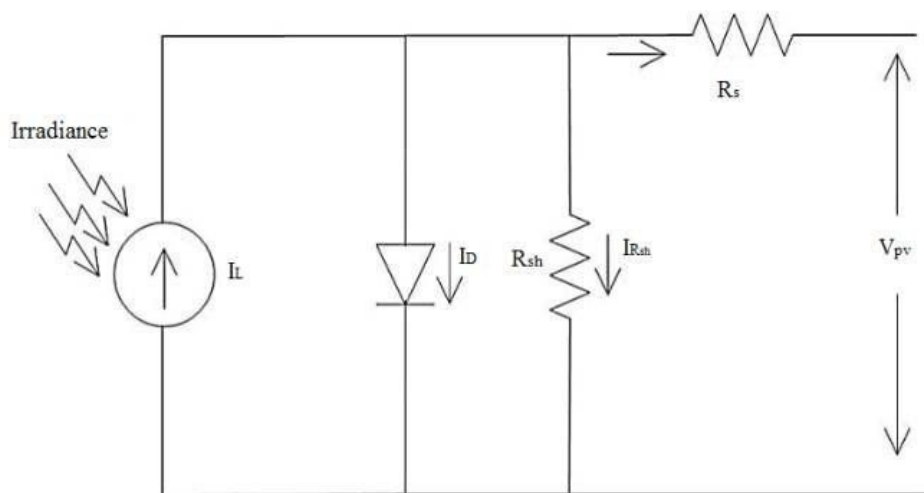


Figure (I. 12): Equivalent Circuit of a PV Cell

Types of Photovoltaic Cells :

Solar panels that use light to make power are made of solar cells. These cells come in different types:

1. Monocrystalline Cells: These are made by melting silicon and letting it cool. When it gets hard, it forms one crystal. This crystal is then cut into thin pieces to make the solar cell. The color is blue, and it looks pure, with no crystals or junk inside.



Figure(I. 13): Monocrystalline Cells

2. Polycrystalline Cells: Polycrystalline silicon is made by melting silicon in a square or long metal mold, creating what's called an ingot. These cells are usually blue with a speckled pattern from the crystals, which makes them easy to spot.



Figure (I. 14): Polycrystalline Cells

3. Hydrogenated Amorphous Cells: Amorphous silicon comes from silicon gas. The gas is turned into vapor on a base like glass, plastic that bends, or metal through a vacuum thing. These solar cells look dark gray.



Figure (I. 15): Hydrogenated Amorphous Cells

I.4 The Impact of Temperature on Solar Panel:

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

- **Reduction in Efficiency:** Solar panels lose some efficiency as they get hotter. They turn sunlight into power, but higher temperatures reduce how well they do this.
- **Voltage Decrease:** As the temperature of a solar panel goes up, its voltage goes down. This happens because the material inside the panel doesn't move charges as well when it gets hot.
- **Power Output Reduction:** Solar panels don't work as well when they get too hot. The heat lowers their efficiency and voltage, which means they produce less power in general.
- **Thermal Degradation:** Over time, high temperatures can break down the materials in solar panels. This lowers how long they last and how well they work.
- **Operating Temperature Range:** Solar panels work best within a specific temperature range. If it gets too hot, they might not work as well.

Basically, solar panels still make power when it's hot, but they don't work as well, which cuts into how much power they produce.

Advantages and Disadvantages of PV Energy:

❖ Advantages:

- **Renewable Energy:** Solar energy is a renewable resource that is found all over the world in great quantity, which makes it a sustainable, long-term source of energy.

- **Low Greenhouse Gas Emissions:** Using solar energy doesn't create greenhouse gases when you use it, which helps lower carbon emissions and fight climate change.
- **Decreasing Costs:** Solar tech costs have gone down a lot over the years. Now, solar power is becoming a real competitor to regular energy sources.
- **Energy Independence:** Solar panel systems let people make their own power, so they don't have to rely as much on energy companies and changing prices..
- **Low Maintenance:** Solar panels don't need much upkeep after they're set up, so you save money on maintenance in the long run.

❖ **Disadvantages:**

- **Sunlight Variability:** Since solar energy relies on sunlight, the amount of electricity it makes changes and isn't consistent. Because of this, you often need ways to store the energy or combine it with power from other sources.
- **High Initial Costs:** Even though solar tech is getting cheaper, setting up solar stuff can still cost a lot upfront.
- **Environmental Impact:** While solar energy is usually thought of as clean, making and getting rid of solar panels can affect the environment.
- **Space Requirement:** Putting in solar panels usually means you need a lot of land surface or roof space for solar panels. This can be tricky in cities or places where space is tight.
- **Dependency on Weather Conditions:** Weather stuff like clouds, rain, or snow can mess with solar system performance. This stuff can lower how well solar panels make power sometimes.

Conclusion:

In this chapter we provided the principles of the solar radiation and the photovoltaic energy conversion. Solar cells use a photovoltaic effect to convert sunlight to electricity. The chapter also outlined the modeling and characteristics of photovoltaic generators, such as temperature dependence, load resistance, and types of photovoltaic cells classified by the crystalline structure of silicon. It also defined the constituent parts of photovoltaic modules and elucidated the strengths and weaknesses of solar photovoltaic technology.

Chapter II

DC-DC Converter

II.1 Introduction :

DC-DC converters are essential circuits in modern power systems, primarily designed to transform direct current (DC) voltage from one level to another. This ensures that power is delivered stably and efficiently to various electronic devices. Even when input voltage fluctuates due to battery discharge or varying load conditions these converters maintain a constant output voltage, providing reliable power to all system components. A major advantage of DC-DC converters is their superior conversion efficiency. By utilizing high-frequency switching, they significantly reduce power losses typically associated with resistive elements or linear regulators, which often generate excess heat and waste energy. This enhancement leads to better overall efficiency and extended battery life for portable electronics. Furthermore, DC-DC converters offer the flexibility to step up or step down voltage levels, enabling precise power distribution. They can also provide galvanic isolation between input and output grounds, mitigating the risk of ground loops and protecting sensitive components from voltage spikes and electromagnetic noise.

II.2 DC-DC Converters :

DC-DC converters are static power electronic devices that transform a fixed DC input into a controllable DC output across a load.

Depending on the power requirements, these converters utilize different switching technologies: thyristors are employed for high-power applications reaching several hundred megawatts with chopping frequencies in the kilohertz range while transistors are preferred for lower power levels (up to 100 kW) to achieve higher switching frequencies of up to 100 kHz.

The following figure illustrates the symbol of a DC-DC converter.

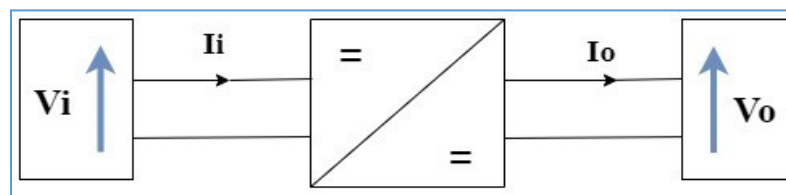


Figure (II. 1): DC-DC Converters

II.3 Applications of DC-DC Converter :

For several years, switch-mode power converters have been widely employed in contemporary electronics across various sectors, including industrial, commercial, utility, and consumer markets. In low-power DC-DC conversion applications, the majority of modern power conversion is achieved through three primary types of power converters: buck, boost,

and buck-boost. However, specialized applications necessitate advanced configurations or modified variations of these conventional topologies.

There are several DC-DC converter types in the literature, but there is no one solution that caters to all the applications. Conversion techniques, in general, have found a wide array of applications in industry, research and development, and daily life[4].

DC-DC converters form a key aspect of study in the field of power electronics and energy drives as they are widely incorporated in several industrial applications. Some of the applications are illustrated in Figure (II.2). High voltage gain converters are employed in multiple sophisticated applications, including radar systems, DC distribution systems, data centers, and harnessing renewable energy[5].

This is especially crucial in the case of renewable energy applications as high voltage gain DC-DC converters facilitate boosting of the voltage that makes it suitable for integration with the distribution system. DC distribution in general offers a multitude of advantages including a reduced number of conversion units, price, and enhanced power quality, making it a preferred choice for a good range of applications.

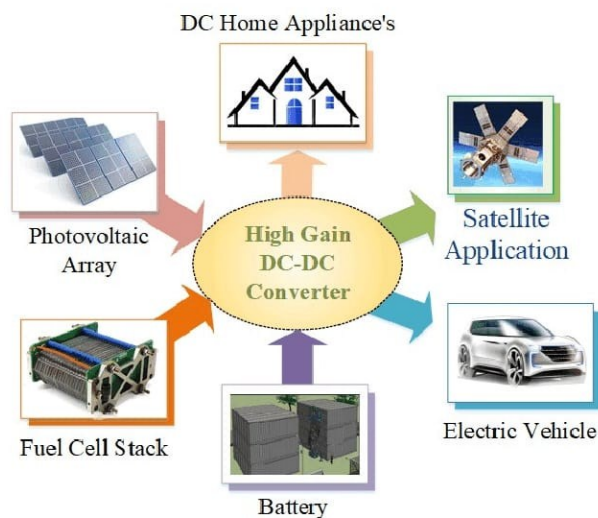


Figure (II. 2) Applications of DC/DC Converters

Here are some of DC-DC converter applications :

- **Renewable energy applications** : DC-DC converters should draw a continuous and smooth input current to reduce ripple. They should also work with different types of power sources. Non-isolated interleaved high voltage gain types are often used to connect renewables and microgrids [6].

- **Medical devices** : In applications where safety is a main concern, isolated DC-DC converters are very important. They separate the output from hazardous input voltages. But, non-isolated converters can work in systems such as x-ray power supplies.
- **Vehicles** : For vehicles, the main DC-DC converter changes the high voltage battery power to lower DC voltages. These lower voltages support things like lights, wipers, and window controls [7]. This is important for both fully electric and hybrid vehicles. Isolation is very important when control systems need to be separate from high voltage areas. Buck-boost converters can either increase or decrease voltage, and charge-pump converters invert voltage.
- **Smart lighting** : LED backlight drivers for quite a few lighting setups have to be highly efficient, control direct current, protect against voltage issues, use pulse-width modulation, and be simply designed. Linear regulators, charge pumps, and standard switching converters can work well as drivers using DC-DC conversion.

II.4 Types of DC-DC converters :

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

II.41. Buck Converter :

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

II.42. Operating Principle of Buck Converter

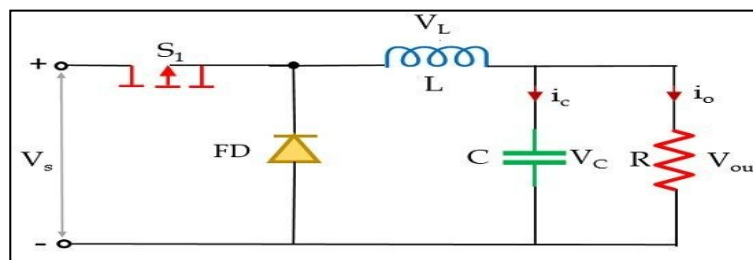


Figure (II.3): The Circuit Representation of Buck Converter

In the above figure, it is clearly shown that along with the power electronics solid-state device which acts as a switch for the circuit, there is another switch in the circuit which is a

freewheeling diode. The combination of these two switches forms a connection with a low-pass LC filter in order to reduce current or voltage ripples. This helps in generating regulated dc output. A pure resistor is connected across this whole arrangement that acts as a load of the circuit.

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

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

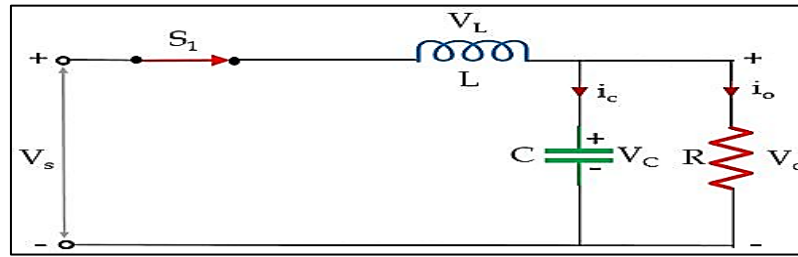


Figure (II.4): Buck Converter When S_1 is Closed

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

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

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

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

The duty cycle is written as:

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

On applying KVL, in the above-given circuit

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

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

Also,

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

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

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

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

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

Hence,

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

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

Now, the second mode of operation takes place when switch 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:

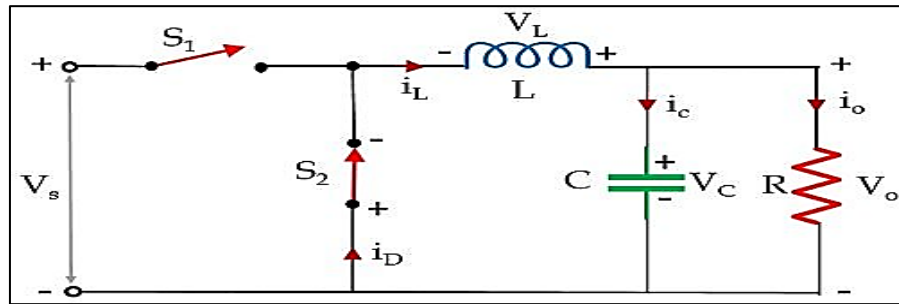


Figure (II.5): Buck Converter When S2 is Closed

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

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

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

Since, we know,

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

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

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

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

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

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

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

So,

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

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,

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

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

On simplifying,

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

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

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

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

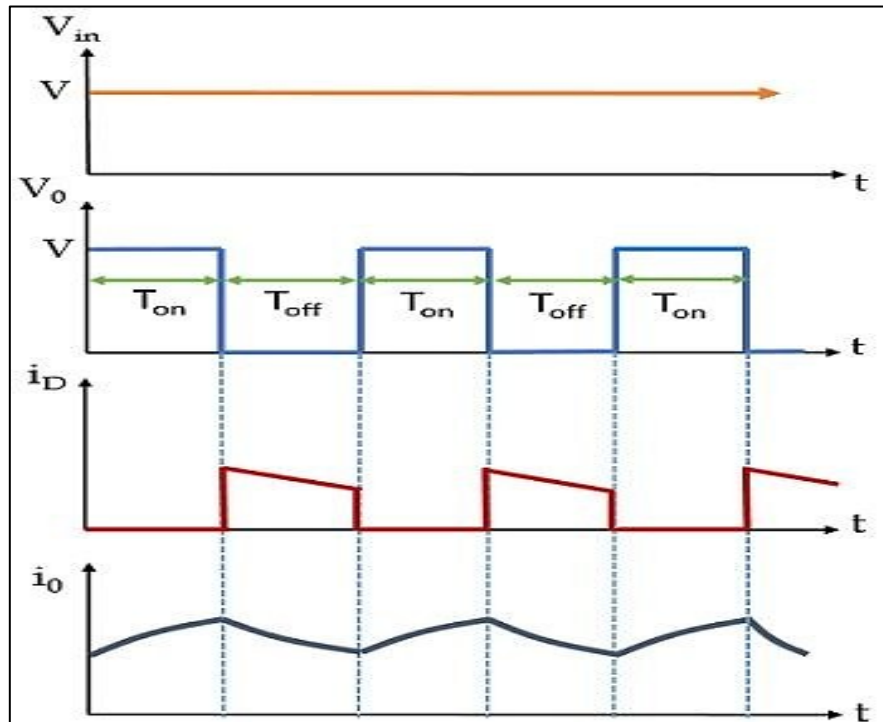


Figure (II.6): Waveform Representation

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

II.43. Boost Converter :

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

II.44. Operating Principle of Boost Converter

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

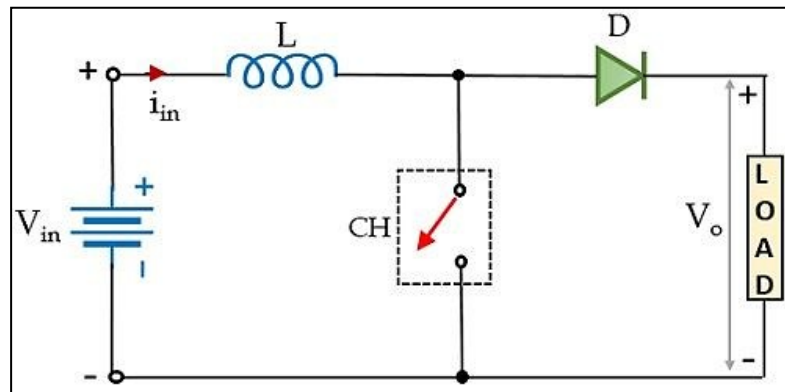


Figure (II.7): Elementary Circuit of Boost Converter

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

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

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

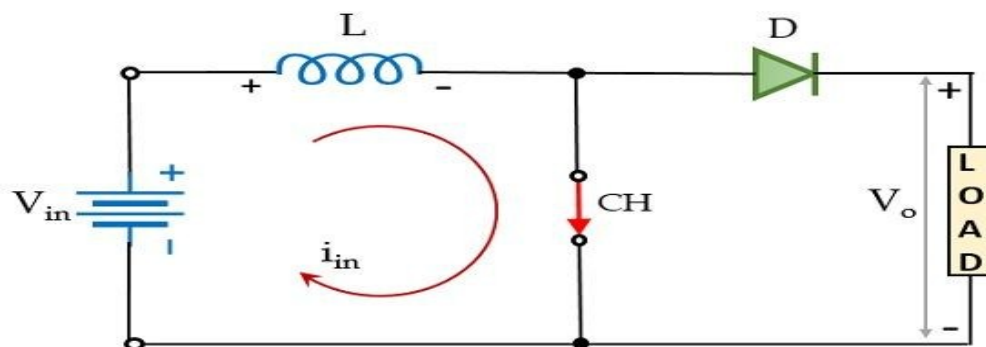


Figure (II.8): The Chopper CH is in on State

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

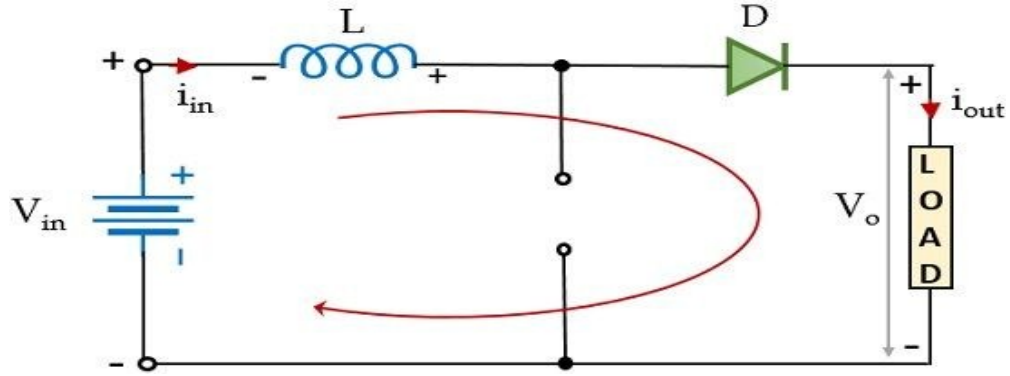


Figure (II.9): The Chopper CH is in Off State

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

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

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

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

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:

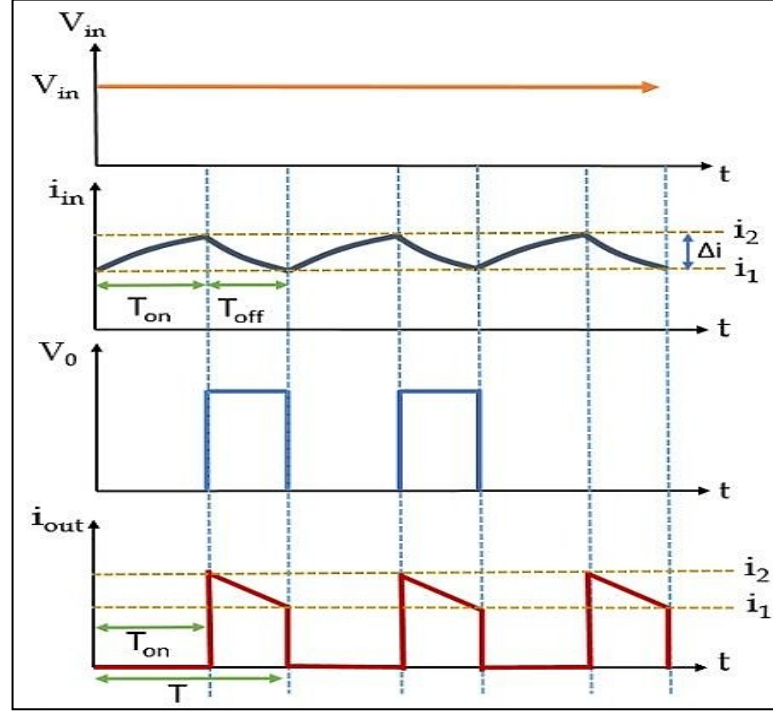


Figure (II.10): Waveform Representation

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

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

This means,

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

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

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

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

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

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

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

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

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

On simplifying,

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

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

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

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

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

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

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

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

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

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

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

II.45. Buck-Boost Converter :

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

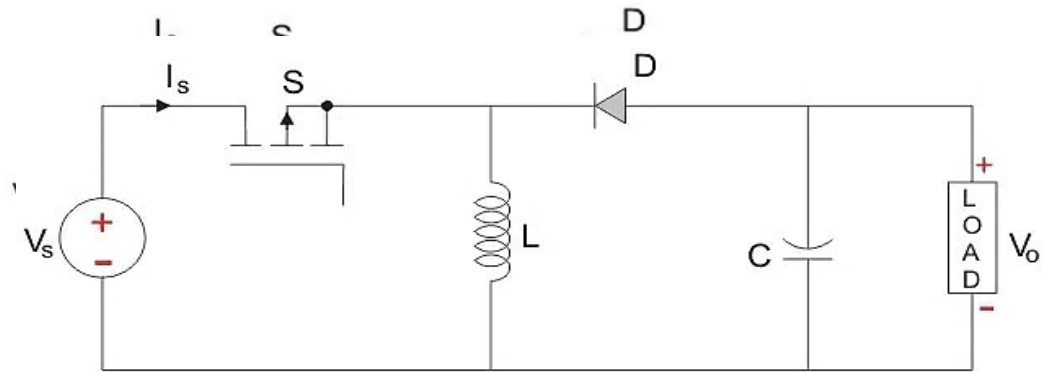


Figure (II.11): The Circuit Representation of Buck-Boost Converter

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

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

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

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

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

Mode I: Switch is ON, Diode is OFF

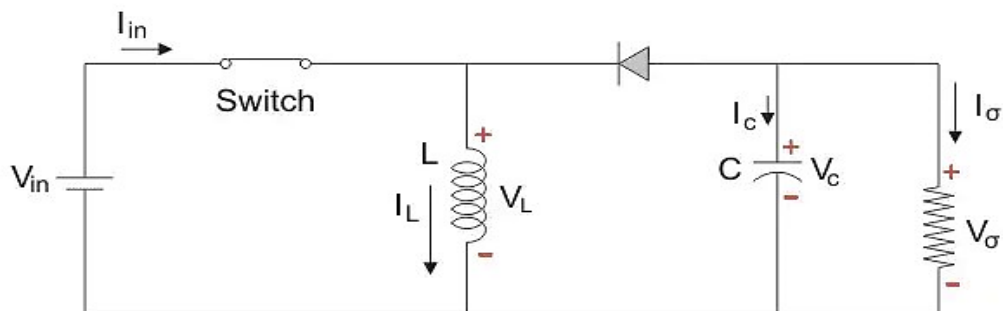


Figure (II.12): The Equivalent Circuit of Mode I

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

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

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

We define the time period, T , as:

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

and the switching frequency:

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

Let us now define another term, the duty cycle:

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

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

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

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

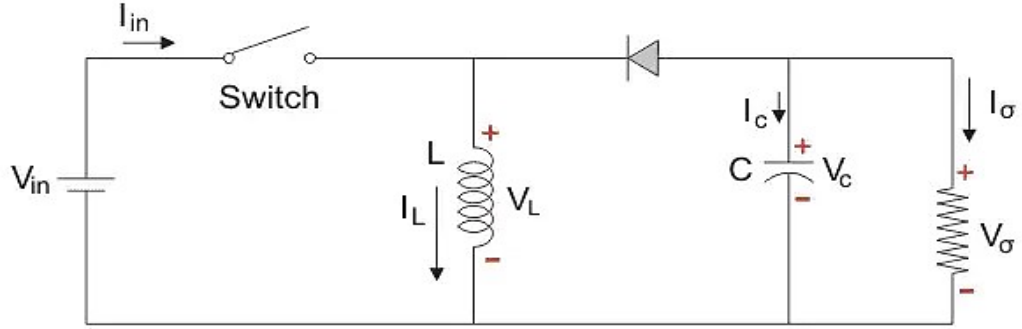


Figure (II.13): The Equivalent Circuit of Mode II

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

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

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

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

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

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

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

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

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].

II.5 Comparison of Converter Types :

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

Table (II.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}	$i_L + \frac{\Delta I_L}{2}$

II.6 Efficiency of Static Converters :

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

Table (II.2): Efficiency of Static Converters.

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

Conclusion :

In this chapter, a comprehensive mathematical modeling of the standalone photovoltaic system has been successfully established. By analyzing the electrical behavior of the PV array under the single diode five parameter model, the non linear relationship between voltage, current, and power was characteristically defined under changing environmental parameters. Furthermore, the dynamic state space equations of the DC-DC Boost Converter were formulated to dictate its critical role in voltage adaptation and impedance matching.

Although this theoretical foundation precisely maps the system's operational characteristics, it explicitly highlights a major challenge: the high vulnerability of the Maximum Power Point (MPP) to variations in solar irradiance and temperature. Consequently, to overcome this limitation and ensure continuous optimal efficiency, integrating an active tracking mechanism becomes paramount. This crucial requirement serves as the fundamental gateway to Chapter III, which will be entirely dedicated to the development and implementation of advanced conventional and intelligent MPPT control strategies.

Chapter III

Maximum Power Point Tracking

Algorithm for PV Systems

III.1 Introduction :

Maximizing solar panel performance requires a holistic approach to system design. Crucially, the DC-DC converters serving as the interface must be optimized to extract peak power through Maximum Power Point Tracking (MPPT). This allows the system to adapt to fluctuating light levels and temperatures, maintaining its Maximum Power Point (MPP) without wasting energy. The landscape of MPPT technology has matured significantly since the 70s; what began as simple feedback loops has evolved into complex algorithmic controls. Among these, the Incremental Conductance (INC), Perturb and Observe (P&O), and 'hill climbing' methods remain the most widely adopted solutions for ensuring consistent energy transfer .

III.2 Maximum Power Point Tracking :

To enhance the overall efficiency of a photovoltaic (PV) system, it is crucial to maximize the power harvested from the PV generator. This is fundamentally a matter of selecting the correct operating point, which involves matching the load impedance to the voltage source. Within this architecture, the DC-DC converter functions as a dynamic impedance adapter; by adjusting this interface, the system can be maintained at its optimal operating point, thereby ensuring peak power production from the PV source [12].

Consequently, maximizing the output of a photovoltaic source requires a continuous search for this optimal state, a process known as Maximum Power Point Tracking (MPPT). These tracking methods utilize iterative search algorithms to pinpoint the solar module's ideal operating point, ensuring peak power generation without disrupting system stability. By monitoring real-time voltage and current measurements to calculate instantaneous power, various control strategies can navigate toward the actual Maximum Power Point (MPP). While several techniques exist including constant voltage, constant current, and incremental conductance algorithms this study adopts the Perturbation and Observation (P&O) method, primarily due to its straightforward implementation and reliable performance.

III.3 Working principle of MPPT :

Control systems are designed to make devices run at their best, even if we don't know what those best settings are ahead of time or if they change. For energy sources,

getting to this point means getting the most power possible. This kind of control is usually called Maximum Power Point Tracking (MPPT). These controls work by seeking the point of top power while keeping the source and load matched so that the most power is transferred.

To make this control easier to operate, a DC load was picked. The chain shows that MPPT control links to a four-pole setup. This setup lets the PV generator and the load adjust to each other. For solar conversion, a DC-DC converter can make this four-pole possible. The power from the PV generator then matches its maximum power (P_{MAX}). After that, it can go right to the load.

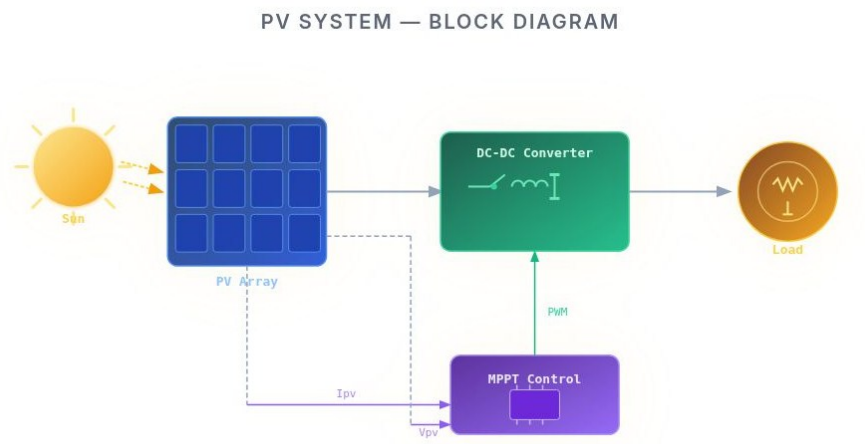


Figure (III1): Block Diagram of The PV System

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 (III2) 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 command. 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 command level, the latter does not have the same time constraints as the previous two cases[14].

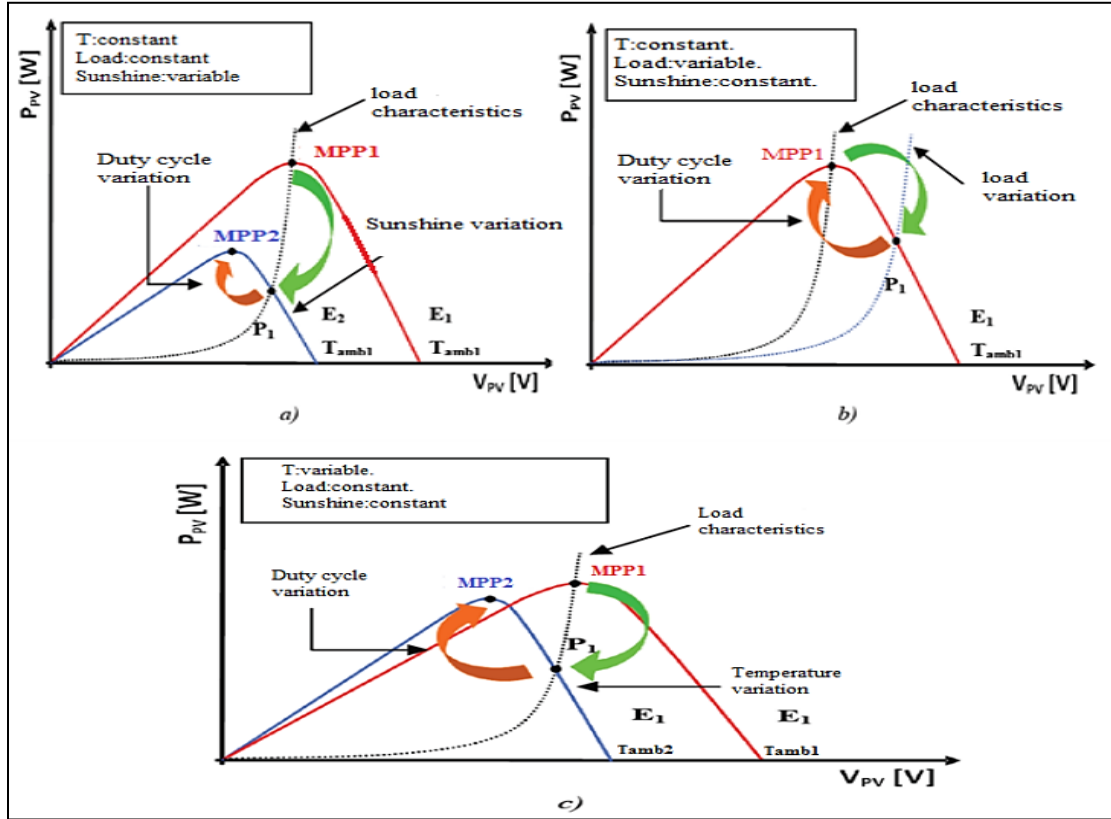


Figure (III2): Search and Recovery Of MPP

III.4 Classification of MPPT Control :

MPPT controllers can be grouped by how they're made analog, digital, or a mix of both. But, it's more useful to group them by what kind of search they do and what info they use.

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

a) MPPT Controllers Operating from Input Parameters :

There are a number of MPPT controllers that perform a maximum power point search according to the evolution of the power supplied by the PV array. Examples include the Perturb and Observe method, incremental conductance algorithms that use the value of the power supplied by the PV array to apply an appropriate control action for MPP tracking, or controllers based on proportional relationships between the optimal parameters characterizing the maximum power point (V_{opt} and I_{opt}) and the characteristic parameters of the PV module (V_{oc} and I_{sc}).

Notably, MPPT controllers inspired by neural networks fall into this category. In these controllers, either large computer memory systems storing all possible cases are used, or the controllers are again approximate. All of these controllers have the advantages of precision and fast response time[15].

b) MPPT Controllers Operating from Output Parameters of the Converter :

Existing research includes algorithms that rely on the output of DC-DC converters. For instance, some MPPT controllers boost output current, which is helpful when the load involves a battery. These systems estimate maximum power via converter . This estimation is more when conversion is more . Still, single-sensor setups tend to lack precision. Many of these setups started in space tech.

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

a) Indirect MPPT :

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

b) Direct MPPT :

This category of MPPT control identifies the optimal Maximum Power Point (MPP) by continuously monitoring the system's current, voltage, or power, allowing for a dynamic response to abrupt changes in operating conditions. Typically, these methods employ iterative search algorithms to track the MPP along the P-V curve without interrupting system operation. By incrementally adjusting the operating voltage, the algorithm evaluates the resulting power output; if the power increases, the search continues in the same direction, whereas a decrease in power triggers a reversal of the search direction. This process causes the operating point to oscillate around the actual MPP.

III.5 Different MPPT Commands Synthesis :

Various works on MPPT commands appear regularly in the literature since 1968, the date of publication of the first command law adapted to renewable energy (photovoltaic). Given the large number of publications in this field, we have a classification of different MPPT according to their basic principles.

III.5.1 First MPPT Commands Types :

The algorithm implemented in the first MPPT command was relatively simple. Indeed, the capacity of microcontrollers available at that time was low and applications, especially, for space had fewer constraints regarding temperature and solar irradiation. The first command to be applied to a photovoltaic system was described by A.F. Boehringer. The command was based on an algorithm of adaptive control, to maintain the system at its maximum power point PPM. This is described in Figure 3 and can be easily implemented on a computer. The system calculates the power at time t_i from the measurements of I_{PV} and V_{PV} , and compares it to the one stored in memory (time $t_i - 1$). From there, a new duty cycle D is calculated and applied to the static converter.

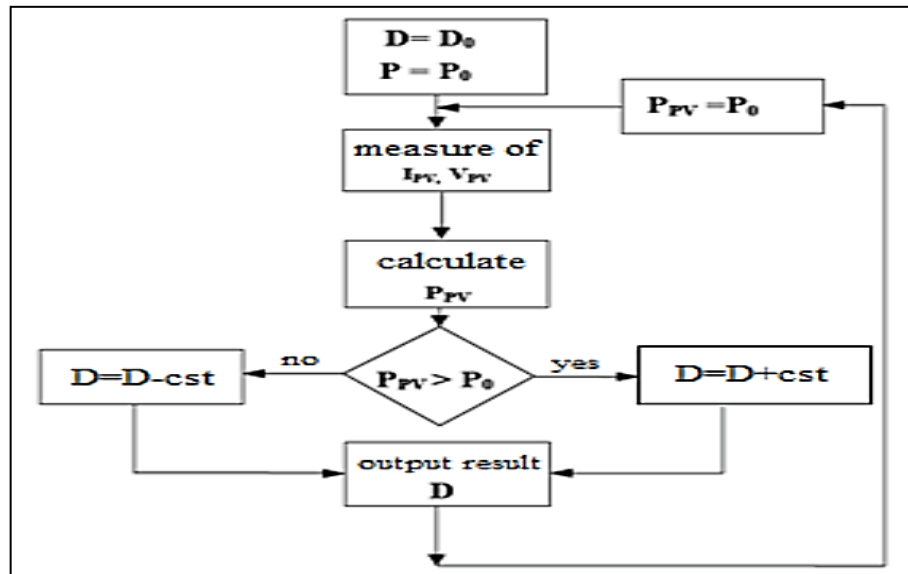


Figure (III3): Bloc Diagram of a Digital MPPT Command

This principle is always valid from a theoretical point of view and applied nowadays to more efficient numerical algorithms. However, the response time has been improved as well as the PPM search accuracy[14].

III.5.2 Efficient MPPT Commands Algorithms :

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

III.5.3 Algorithm Perturb and Observe (P&O) :

The principle of MPPT commands of P & O types is to disrupt the voltage V_{PV} with a low amplitude around its initial value and analyse the behaviour of the resulting power variation P_{PV} . Thus, as shown in Figure (III4), we can deduce that if a positive increment of voltage V_{PV} generates an increase of power P_{PV} , this means that the operating point is to the left of the MPP. If, however, the power decreases, this implies that the system has exceeded the MPP.

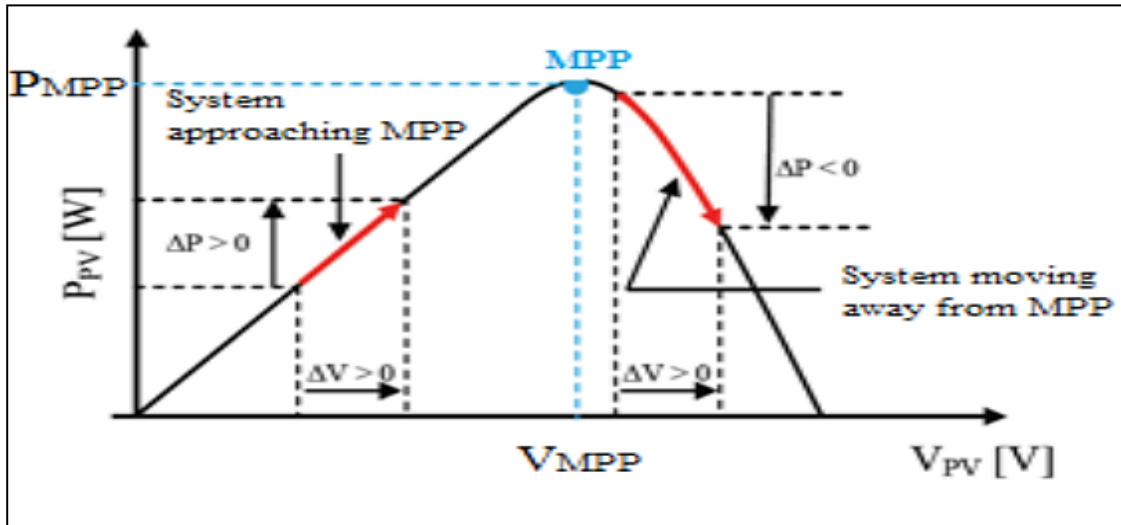


Figure (III5): Algorithm of The P&O Command Due to Radiation Variations

shows the algorithm associated with a conventional MPPT command of the P & O type, where the evolution of the power is analyzed after each voltage disturbance. For this type of command, two sensors (current and voltage) are needed to determine the power of the solar generator at every instant of time. The Perturb & Observe method is nowadays widely used because of its ease of implementation. However, it has some problems associated with oscillations around the MPP it generates in steady state

because the search of the MPP should be repeated periodically, causing the system to oscillate continuously around the MPP.

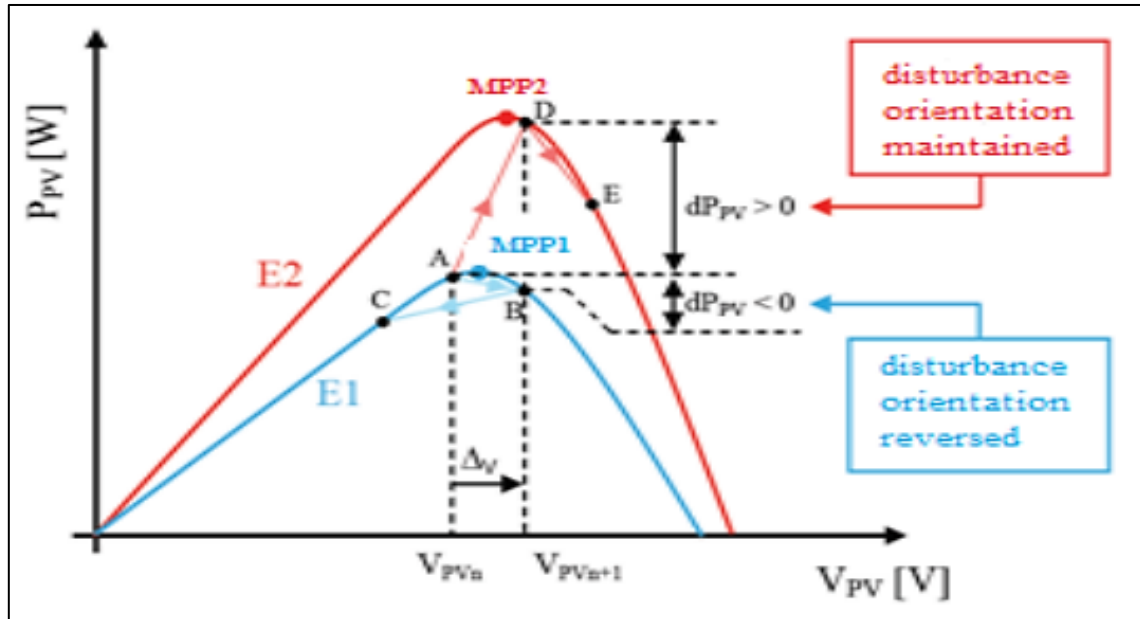


Figure (III.5): Divergence of The P & O Command Due to Radiation Variations

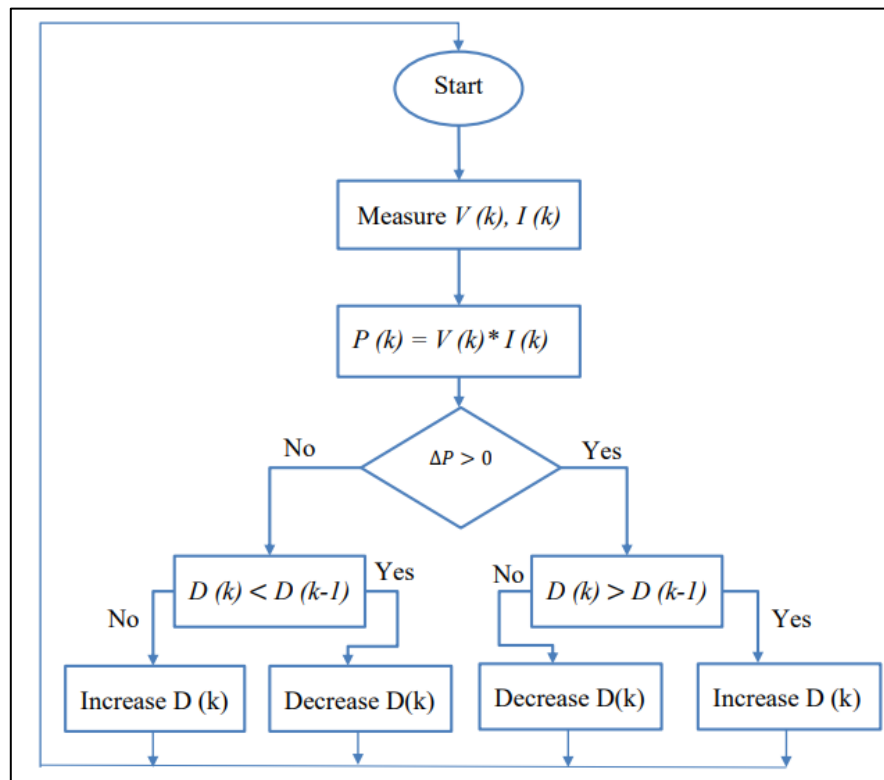


Figure (III.6): Algorithm of The P & O Type of Command

To understand this, consider the example of a given solar irradiation, E_1 , with an operating point lying in A. following a voltage disturbance of value ΔV , it switches to B, implying a variation of operating without illumination, a reversal of the sign of the disturbance due to the detection of a negative sign for the derivative of the power resulting, in equilibrium, in oscillations around the Maximum Power Point due to the path of the operating point between points B and C. it can be noted that losses of power transfer will be more or less important depending on the respective positions of points B and C with respect to A. When changing the irradiation of the module from E_1 to E_2 , the operating point then moves from A to D, which is interpreted in this case as a positive power variation[14].

III.5.4 Algorithm Hill Climbing :

The best thing about the hill climbing MPPT method is its simplicity. It uses the duty cycle of the boost converter as feedback parameter when the task of the MPPT is carried out[17],[18]. The main disadvantage of this technique is due to the trade-off between the stability of the system in a period of constant irradiation. Another disadvantage is the absence of a rapid response in case of a rapid change in radiation[17],[18]. The period of steady radiation requires a very small value of variation in the duty cycle, ΔD to avoid a strong oscillation of the power about the peak power point, reducing the energy captured by the PV. On the other hand, rapidly changing irradiation requires a higher duty cycle value to accelerate the pursuit of peak power.

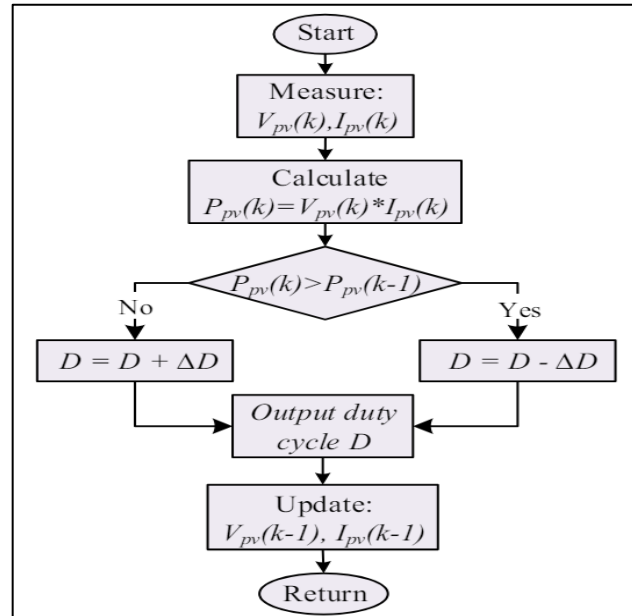


Figure (III7): State Flowchart of Hill Climbing MPPT Technique.

III.5.5 Algorithm Incremental conductance (INC) :

The principle of this algorithm is based on knowledge of the conductance value $G=I/V$ and the conductance increment (dG) in order to deduce the position of the operating point relative to the maximum power point. If the conductance increment (dG) is greater than the negative of the conductance ($-G$), the duty cycle is decreased. On the other hand, if the conductance increment is less than the negative of the conductance, the duty cycle is increased. This process is repeated until the maximum power point is reached[19].

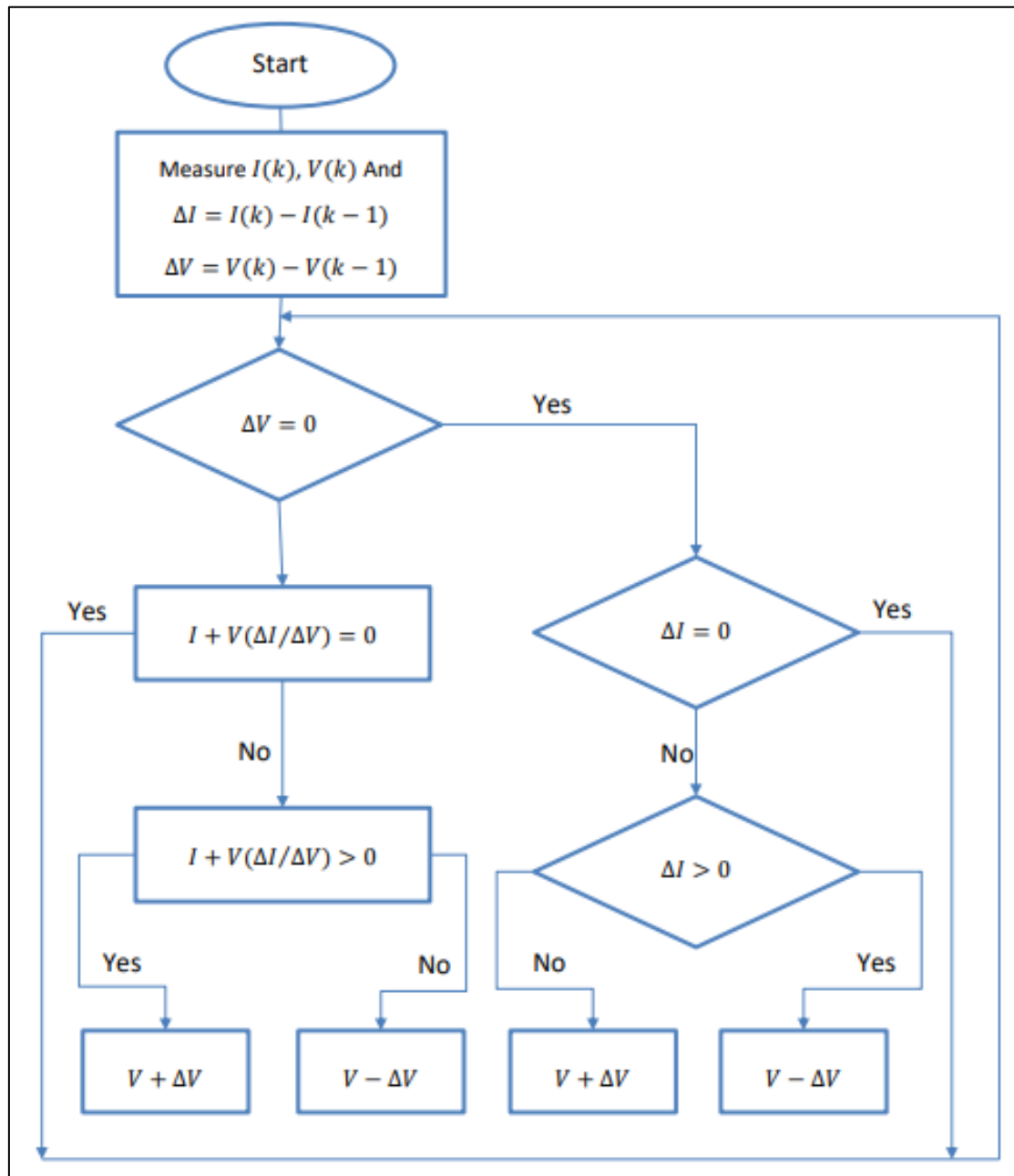


Figure (III8): Flowchart for The Incremental Conductance Algorithm.

III.5.6 Artificial Neural Networks (ANN) :

Generally, an artificial neural network utilizes numerous processors working simultaneously and arranged in different layers. The initial layer takes in raw data inputs, similar to how the optic nerves receive visual information in humans.

Afterward, each subsequent layer receives the processed outputs from the previous layer. This process resembles the human experience, where neurons receive signals from neurons closer to the optic nerve. The final layer, however, generates the system's ultimate results or outputs.

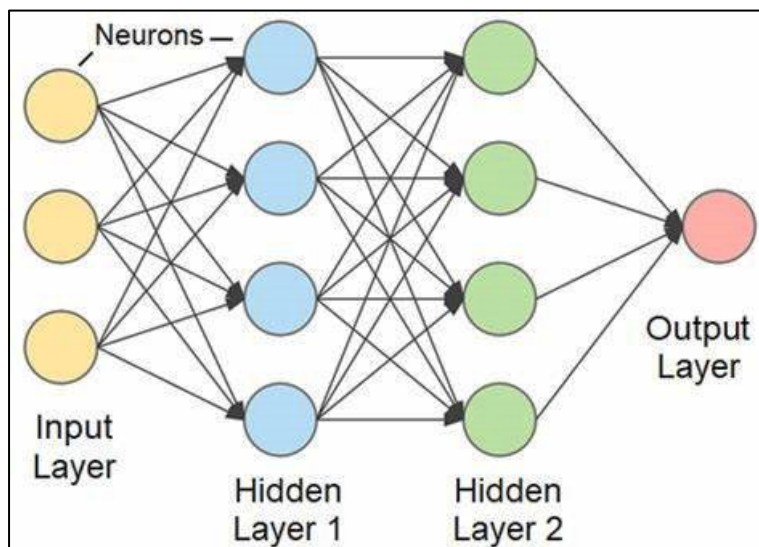


Figure (III9): Functioning of Artificial Neural Networks

Neural networks enable computers to learn from new data through algorithms. Computers with neural networks are trained on labeled example data to learn tasks like object recognition by analyzing patterns in the examples. Unlike traditional algorithms, neural networks cannot be directly programmed - they learn in a similar way to a child's developing brain. There are three main learning methods:

1. **Supervised Learning** : The algorithm trains on labeled data and adjusts until it can achieve the desired output.
2. **Unsupervised Learning** : The network analyzes unlabeled data, with a cost function guiding it towards the desired result by indicating deviations.
3. **Reinforcement Learning** : The network is rewarded for positive results and penalized for negative ones, enabling it to learn and improve over time like humans learn from mistakes.

III.5.7 Application of Artificial Neural Networks in MPPT :

Artificial neural networks are employed to optimize maximum power point tracking (MPPT), a crucial element in photovoltaic (PV) systems. They improve the efficiency of capturing solar energy by continuously adjusting the operating point of the PV panels to maximize their power output. This adjustment accounts for changing environmental factors like solar radiation levels, temperature, and shading conditions. By doing so, neural network-based MPPT enables PV systems to more effectively harness solar energy and increase their overall energy production.

This example shows the use and practical application of artificial neural networks and their valuable role in improving the performance of PV systems through MPPT algorithms[20].

III.5.8 Implementation of ANN in MATLAB/SIMULINK :

The Neural Network Fitting app in MATLAB provides a user-friendly interface for designing, training, and evaluating artificial neural networks. The process involves selecting the data, configuring the network architecture, training the network, and assessing its performance through various plots and metrics. This tool is particularly useful for tasks like MPPT, where accurate modeling of complex relationships between inputs and outputs is crucial.

1. Data Collection :

The initial phase of the proposed method involves collecting data from MPPT method simulations performed under a variety of scenarios. Data collection is the cornerstone for training and evaluating the ANN-based MPPT model[20].

2. Setting Up the Neural Network Fitting Tool :

To begin the implementation process, we will open the Neural Network Fitting Tool in MATLAB. This tool provides a user-friendly interface for training and evaluating neural networks. We will import our defined variables and configure the tool for our specific application[21].

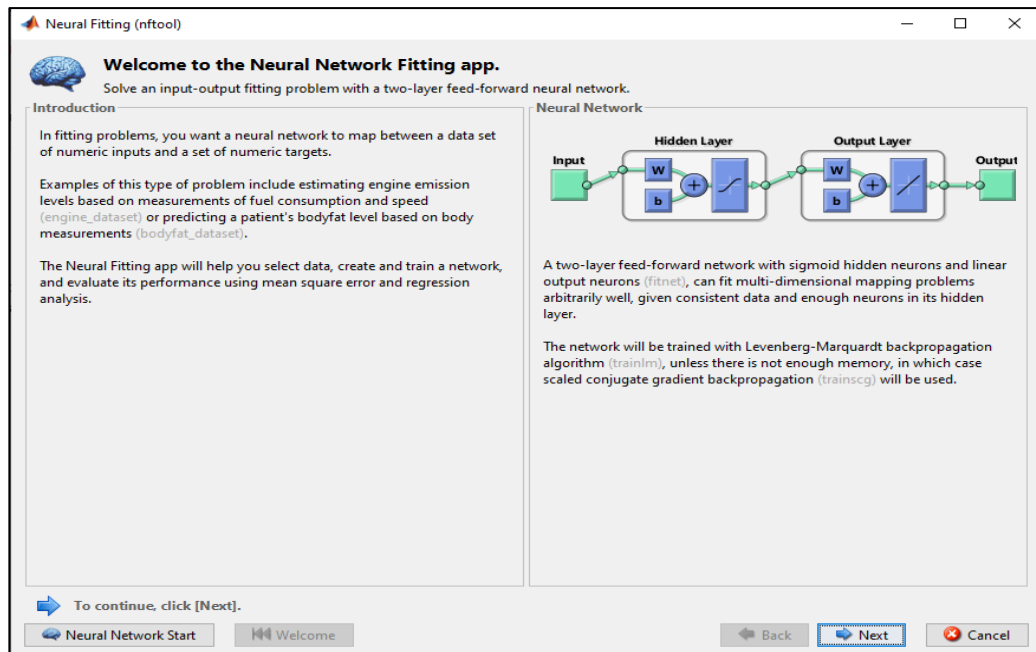


Figure (III10): Setting Up the Neural Network Fitting Tool

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

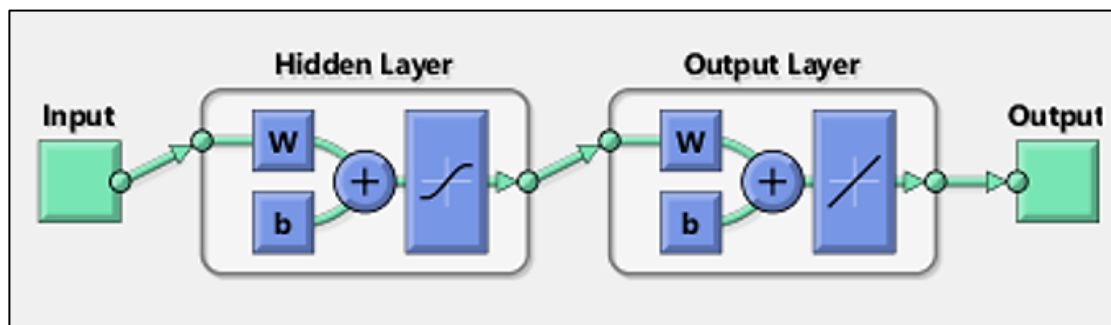


Figure (III11): Neural Network Structure 1

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

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

3. Select Data :

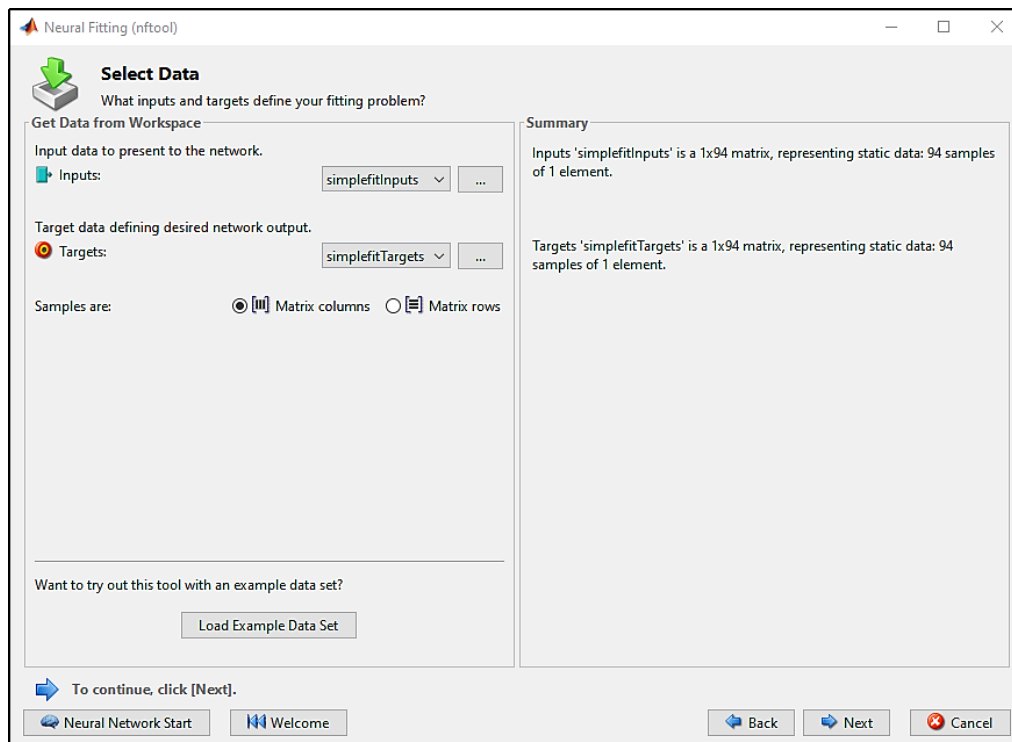
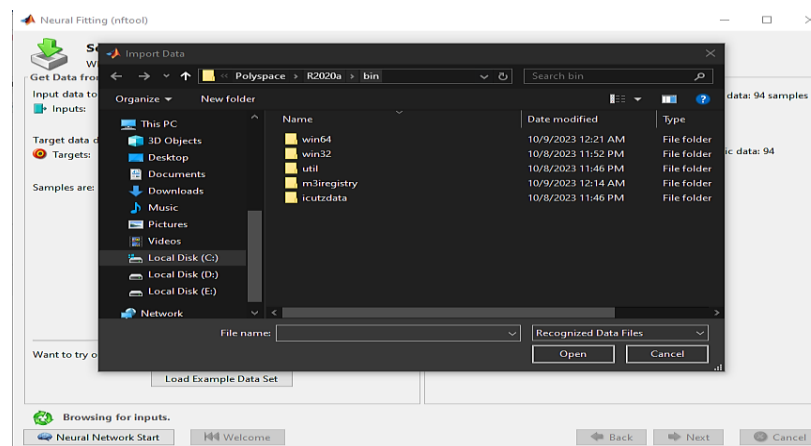


Figure (III.12): Select Data

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.



Import Data :Figure (III.13): Import Data

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

4. Validation and Test Data :

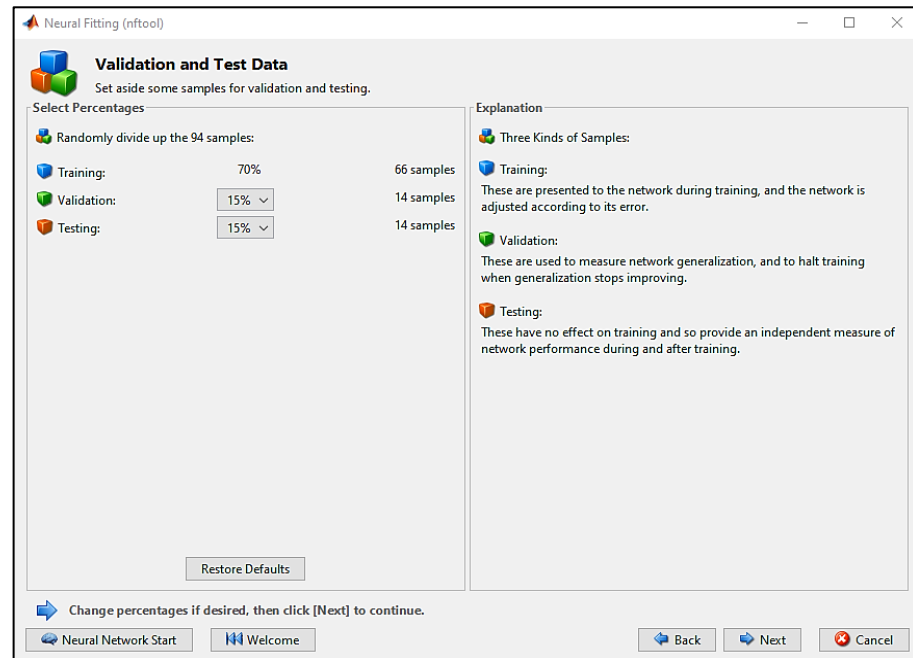


Figure (III14): Validation and Test Data

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. Network Architecture :

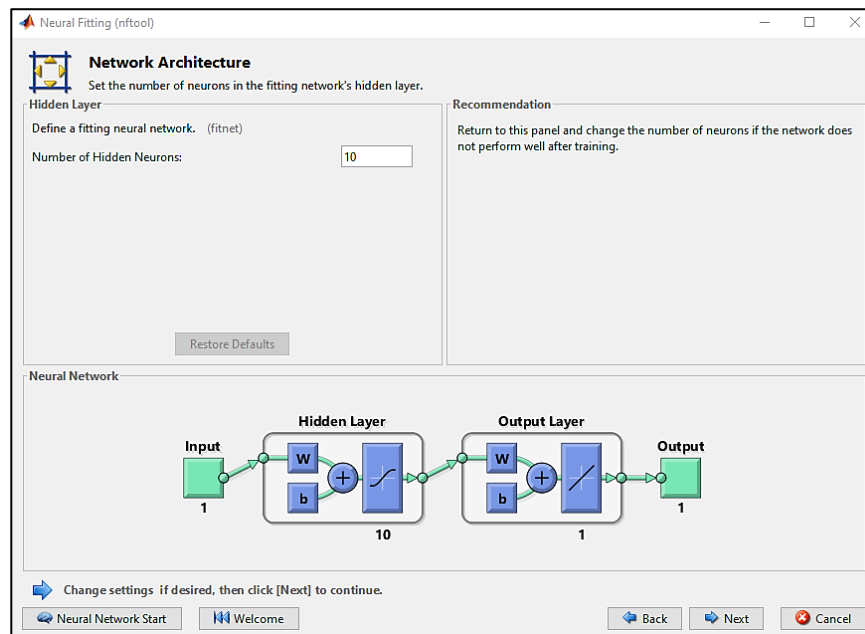


Figure (III15): Network Architecture

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

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

Network Training:

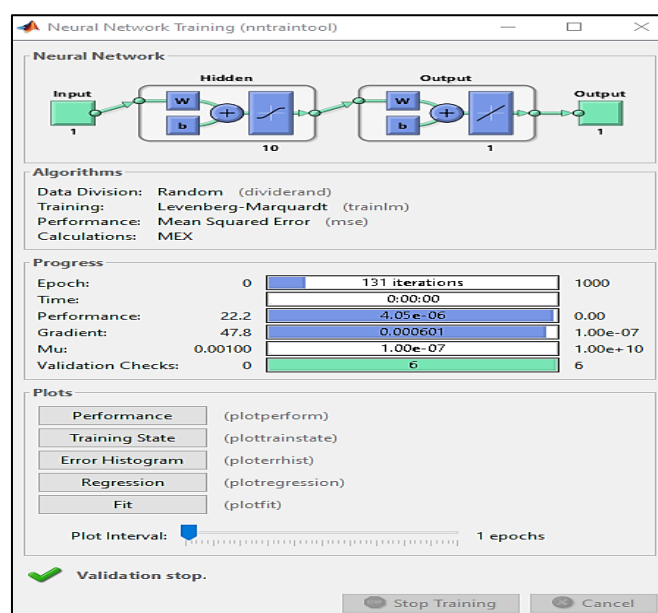


Figure (III16): Network Training

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].

7. Train Network :

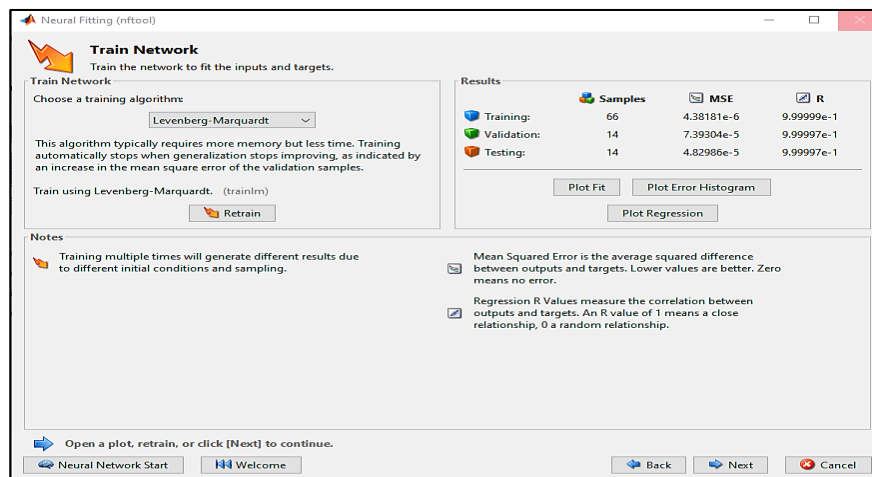


Figure (III17): Train Network

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

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

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

Conclusion :

This chapter has addressed one of the most critical aspects of the current study: the fundamental principles of Maximum Power Point Tracking (MPPT) and the classification of its various control strategies. By detailing the most prominent MPPT methodologies found in the literature, it becomes evident that this field remains in a state of constant evolution. The diversity of existing control laws suggests that a single, universal solution remains elusive, as each method presents unique trade-offs between complexity, cost, and tracking efficiency.

Chapter IV

Simulation Results

IV.1 Introduction :

This chapter presents a detailed evaluation and comparison of three widely employed Maximum Power Point Tracking (MPPT) algorithms: Perturb and Observe (P&O), Incremental Conductance (INC), and Artificial Neural Network (ANN). These algorithms are integral to optimizing the power output of photovoltaic (PV) systems by dynamically adjusting the operating point to extract the maximum possible energy from solar modules. Precise tracking of the maximum power point is critical for enhancing the overall efficiency and energy yield of PV systems. The P&O algorithm operates through systematic perturbations followed by observations to approach the optimal operating point, while the INC method refines this process by utilizing incremental conductance for more precise adjustments. In contrast, the ANN algorithm employs artificial intelligence techniques to predict and track the maximum power point with a high degree of accuracy. This comparative analysis seeks to elucidate the respective advantages and limitations of each algorithm, thereby offering informed guidance regarding their applicability under varying operational conditions.

IV.2 Parameters of System Simulation :

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

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

Figure (IV.1): Characteristics of Panel

Table (IV.1): Parameters of Boost Converter

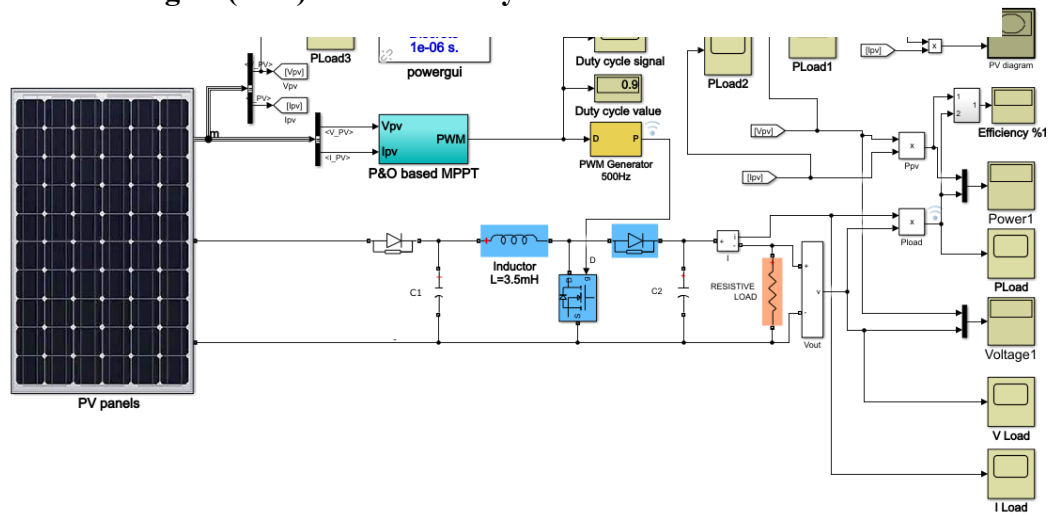
Boost Converter	Value
Capacitor 1	200 μ F
Inductor	3.5 mH
Capacitor 2	100 μ F
Resistive Load	300 Ω

IV.3 Simulation Results :

IV.3.1 P&O Algorithm :

In this simulation, the Perturb and Observe (P&O) algorithm was employed to derive the power, voltage, and current outputs. Figure (IV.2) depicts the overall system simulation, illustrating the configuration and operational characteristics of the MPPT system based on the P&O method. The figure demonstrates the integration of photovoltaic panels with the P&O-driven MPPT controller, which modulates the duty cycle to enhance power extraction efficiency.

figure(IV.2) : Schema of System Simulation With P&O



rradiance (1000 W/m^2) :

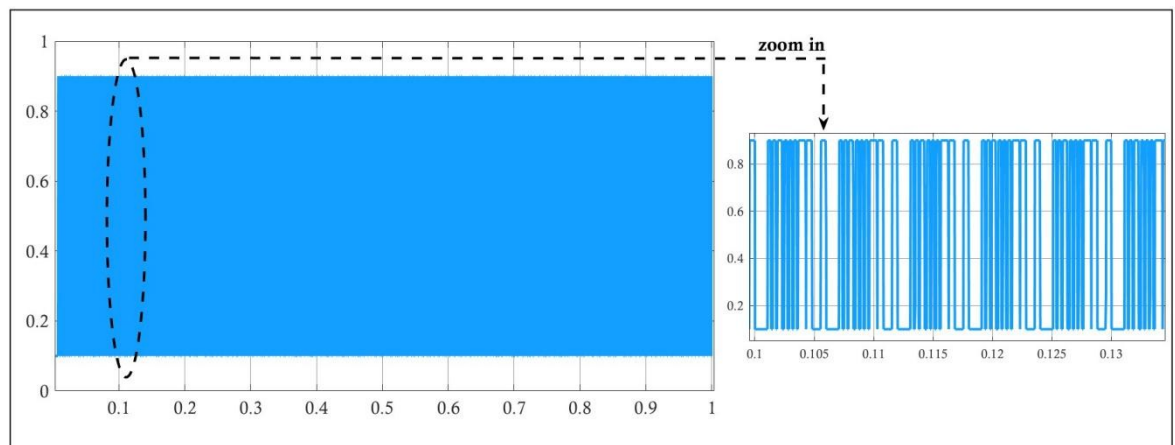


Figure (IV.3): Duty Cycle Simulation Result

The Figure (IV.3) 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.

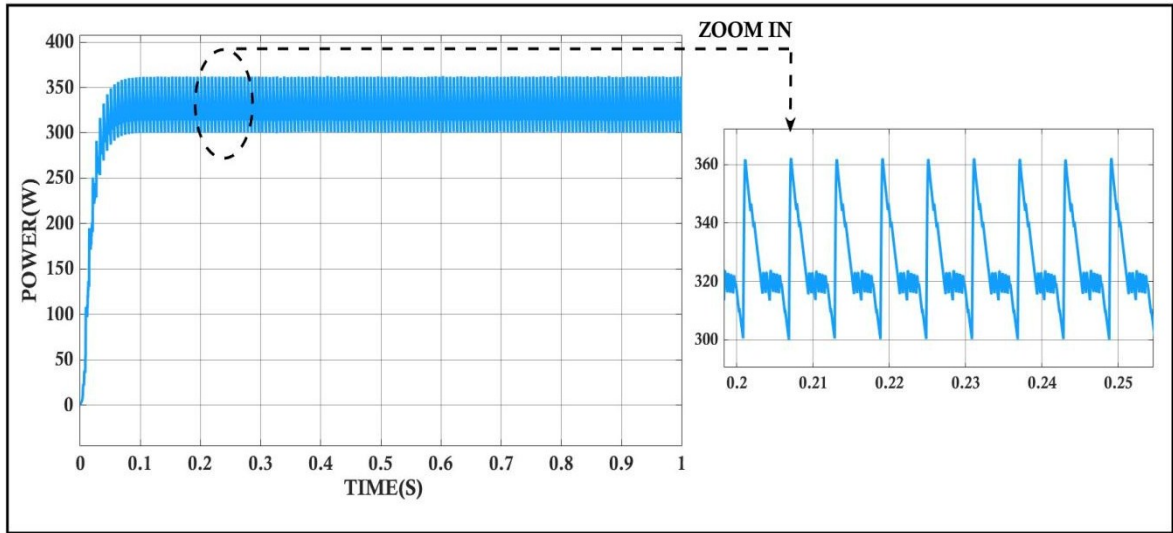


Figure (IV.4): Power Simulation Result

Figure IV.4 presents the power response of a maximum power point tracking (MPPT) system employing the perturb and observe (P&O) algorithm. The primary curve demonstrates a swift rise in power, subsequently stabilizing near 350 W. A magnified section reveals the inherent oscillations in power output, which are typical of the P&O method due to its ongoing perturbations aimed at locating the maximum power point. These fluctuations represent a compromise necessary for achieving near optimal power extraction and play a significant role in assessing the overall efficiency and performance of the MPPT system.

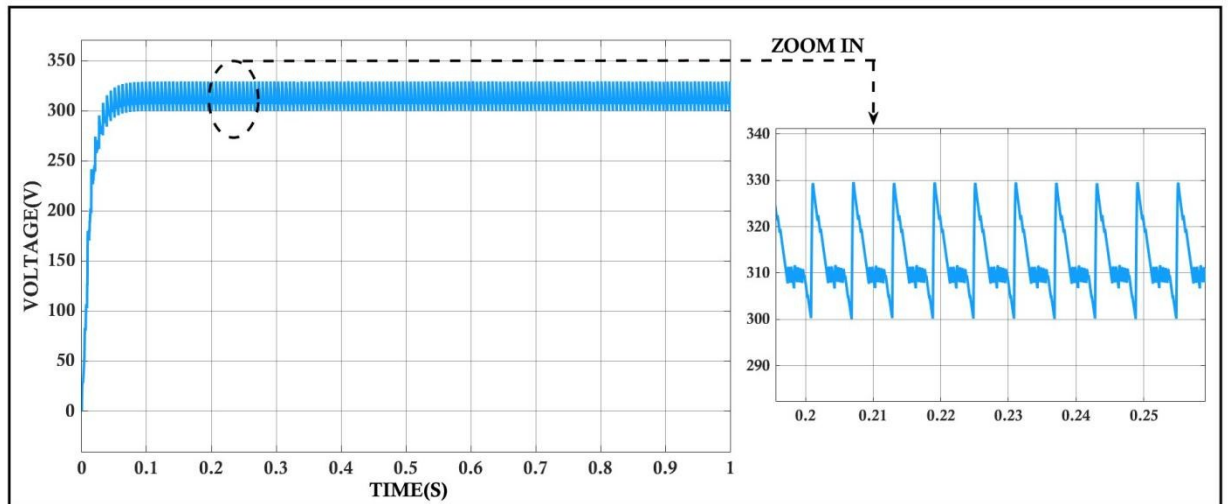


Figure (IV.5): Voltage Simulation Result

The Figure (IV.5) illustrates the voltage response of an MPPT system using the P&O algorithm. The main plot shows a rapid increase in voltage, stabilizing around 320V. The zoomed-in view highlights the oscillatory nature of the voltage output.

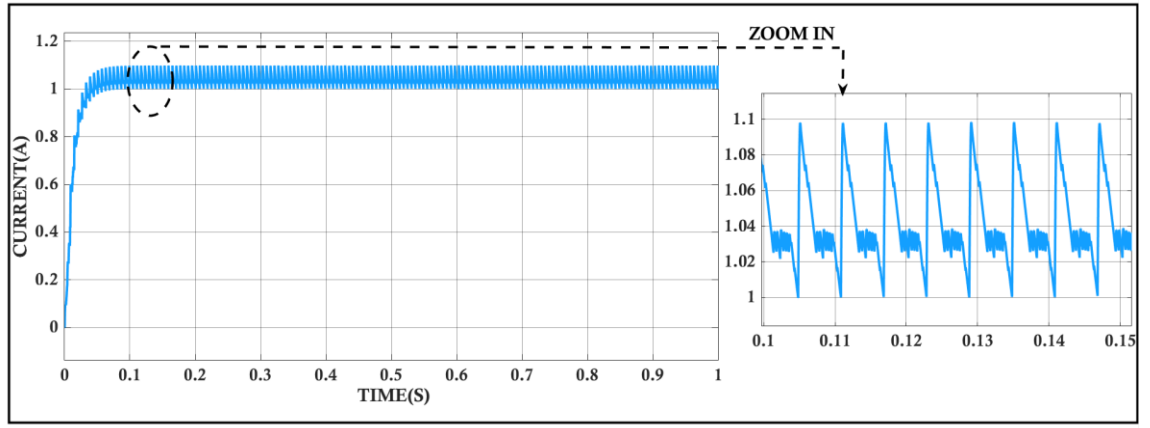


Figure (IV.6): Current Simulation Result

The Figure (IV.6) illustrates the current response of an MPPT system using the P&O algorithm. The main plot shows the rapid transient response leading to stabilization at approximately 1.05A, indicative of the system reaching its maximum power point. The zoomed-in view provides a closer look at the inherent oscillations around this steady-state value.

b) Variable Irradiances (1000, 800, 600, 900 W/m²) :

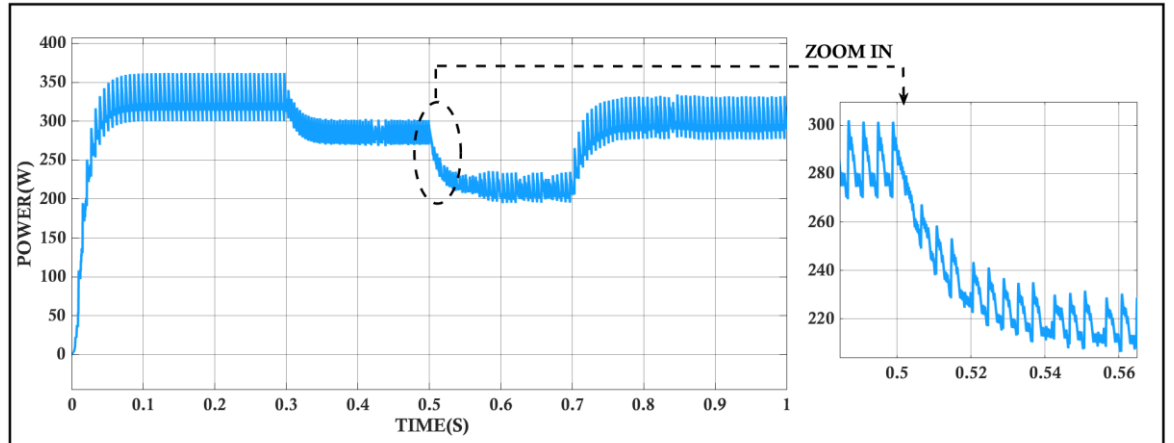


Figure (IV.7): Power Simulation Result

Figure IV.7 presents a detailed characterization of the MPPT system's power output under varying irradiance conditions. The primary plot illustrates the system's capacity to track the maximum power point across different irradiance levels, with power output stabilizing near 350 W, 300 W, 250 W, and 200 W corresponding to irradiance values of 1000 W/m², 800 W/m², 600 W/m², and 900 W/m², respectively. The inset, highlighted by a red dashed ellipse, focuses on the transient response following a sudden decrease in irradiance, revealing typical oscillatory behavior as the perturb and observe algorithm converges to the updated maximum power point. This analysis provides insight into the MPPT system's dynamic performance and its ability to maintain efficiency in real-time solar energy harvesting scenarios.

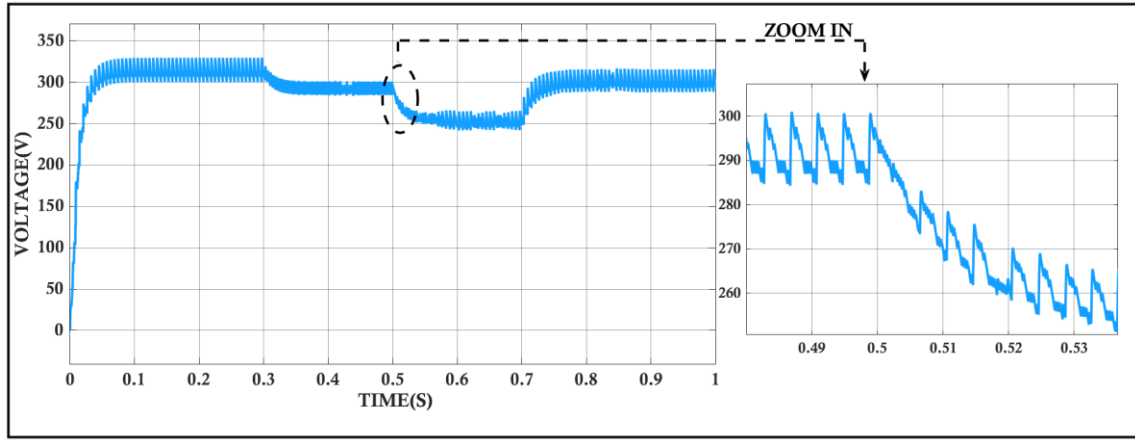


Figure (IV.8): Voltage Simulation Result

Figure IV.8 illustrates the voltage response of an MPPT system employing the P&O algorithm under varying irradiance conditions. The primary graph highlights the rapid stabilization of the voltage near 320 V, after which discrete declines occur corresponding to reductions in irradiance. The inset offers a closer examination of transient voltage variations, demonstrating the algorithm's ongoing adjustments aimed at preserving optimal operation.

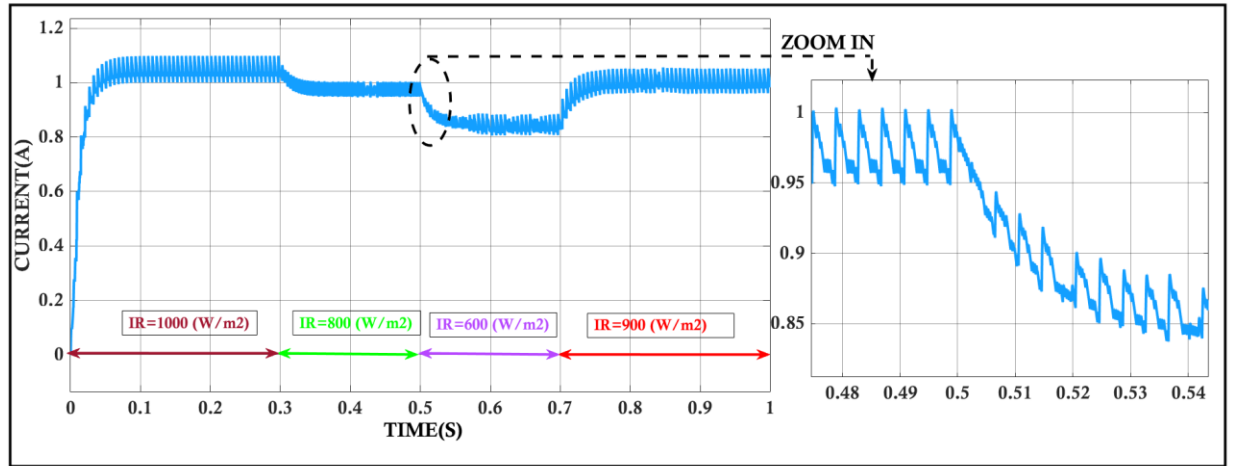


Figure (IV.9): Current Simulation Result

The Figure (IV.9) demonstrates how the MPPT system's current output, managed by the P&O algorithm, adjusts under varying irradiance levels. The main plot shows the current stabilizing around 1A and decreasing in steps as irradiance diminishes. The zoomed-in view captures the transient response during an irradiance change.

IV.3.2 Incremental Conductance :

In this simulation, the Incremental Conductance (INC) algorithm was employed to derive the power, voltage, and current outputs. Figure IV.10 depicts the overall system simulation, highlighting the configuration and operational behavior of the MPPT system based on the INC method. This figure demonstrates the integration of photovoltaic panels with the INC-driven MPPT controller, which modulates the duty cycle to enhance power

extraction

efficiency.

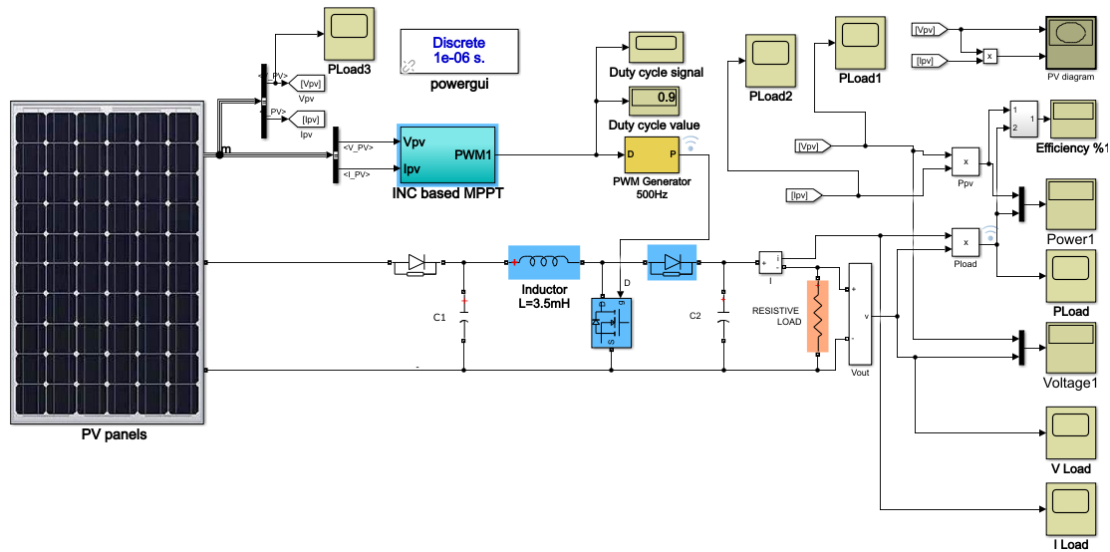


Figure (IV.10): Schema of System Simulation With INC

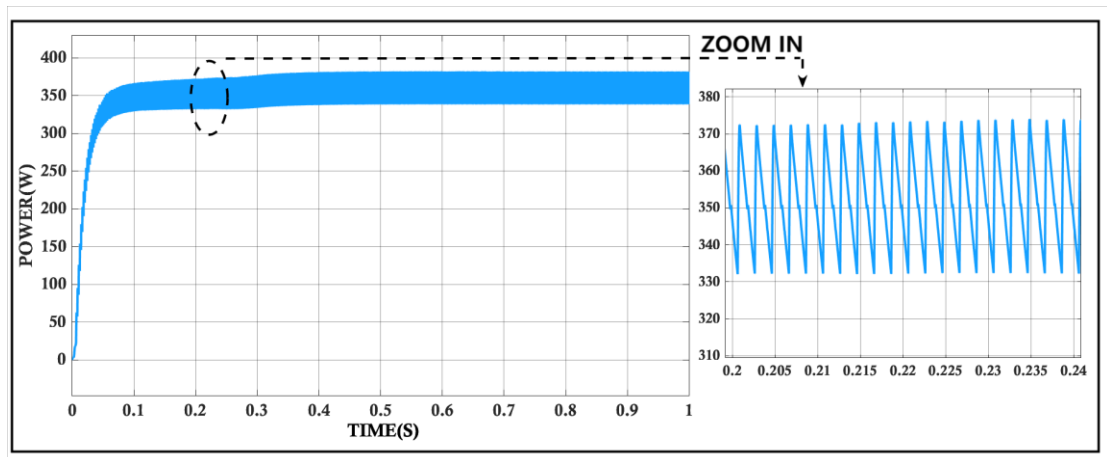
a) Constant Irradiance (1000 W/m^2) :

Figure (IV.11): Power Simulation Result

Figure IV.11 illustrates the power stabilization characteristics of a maximum power point tracking (MPPT) system regulated by the Incremental Conductance algorithm. The primary graph depicts a swift increase in power, stabilizing around 370 W, which indicates the system's effective energy capture. A magnified section reveals periodic oscillations, demonstrating the algorithm's ongoing adjustments to sustain near-optimal power output. This observation highlights the algorithm's ability to dynamically and accurately track the maximum power point under varying conditions.

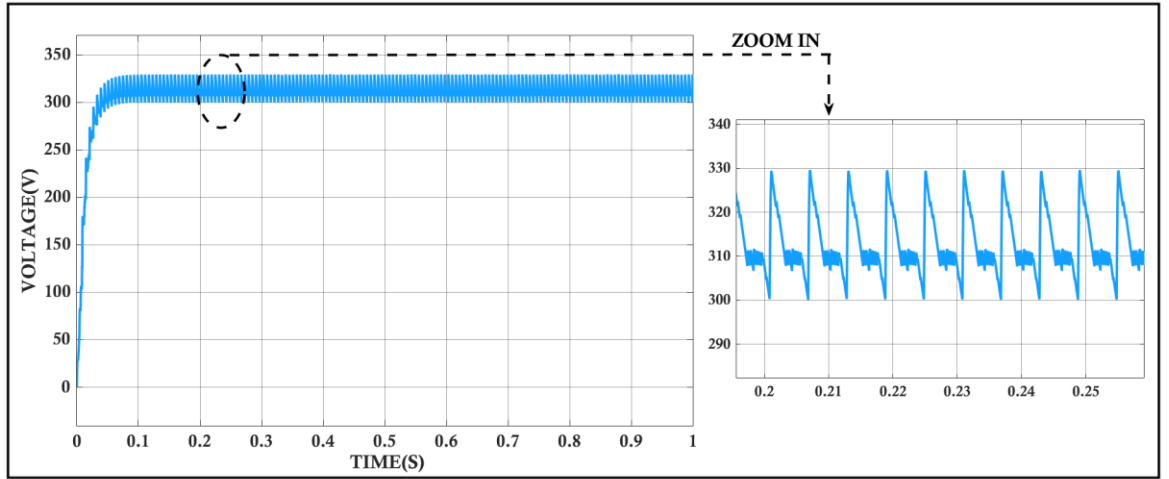


Figure (IV.12): Voltage Simulation Result

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

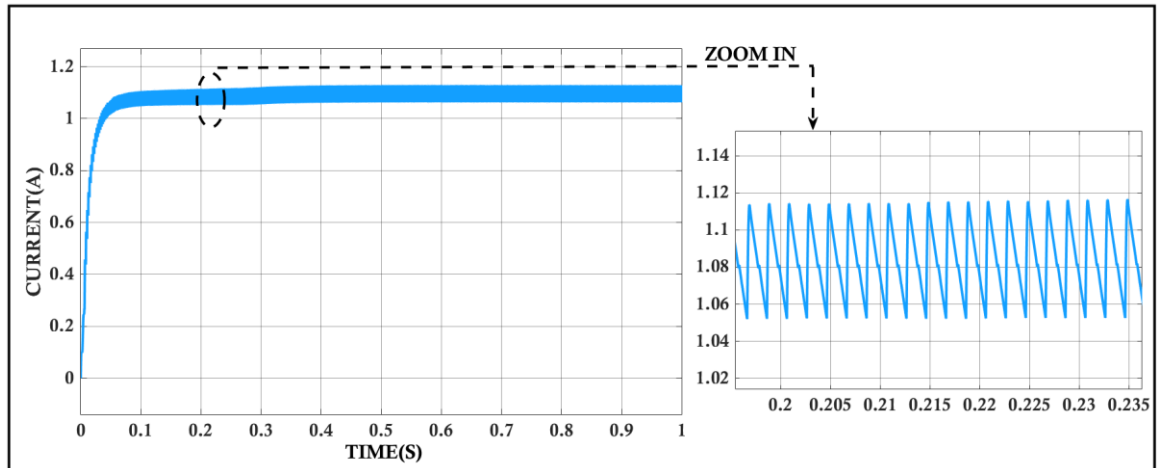


Figure (IV.13): Current Simulation Result

Figure IV.13 illustrates the current stabilization characteristics of an MPPT system controlled by the Incremental Conductance algorithm. The primary graph reveals a rapid increase in current, which stabilizes near 1.1A, reflecting the system's effectiveness in approaching the maximum power point. The inset provides a detailed view of minor current variations during the steady state.

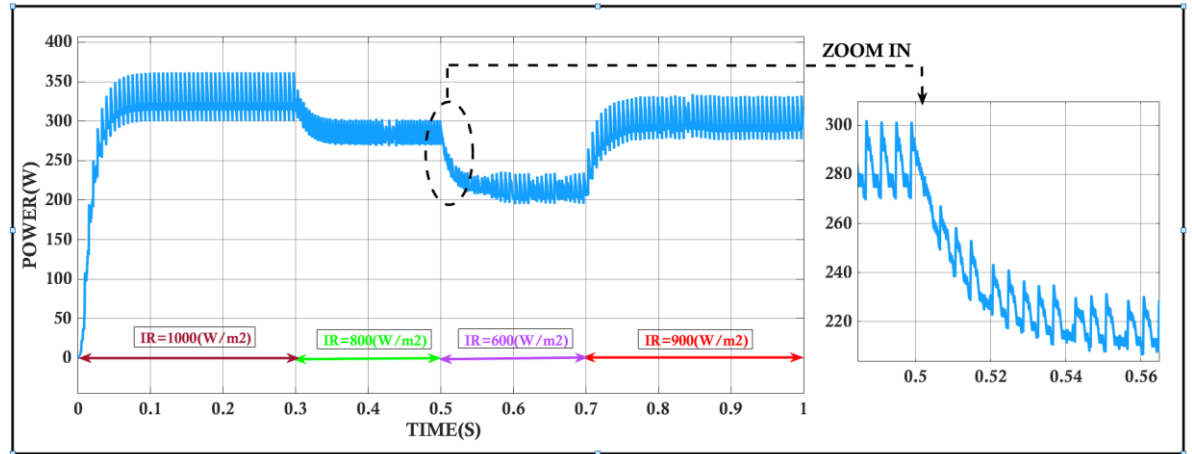
b) Variable Irradiances (1000, 800, 600, 900 W/m^2) :

Figure (IV.14): Power Simulation Result

Figure IV.14 presents the power response of a maximum power point tracking (MPPT) system implemented with the Incremental Conductance algorithm under fluctuating irradiance conditions. The primary graph illustrates the power output initially stabilizing near 350 W, followed by discrete reductions corresponding to decreases in irradiance. An inset detail provides a closer examination of the transient variations occurring during changes in irradiance levels.

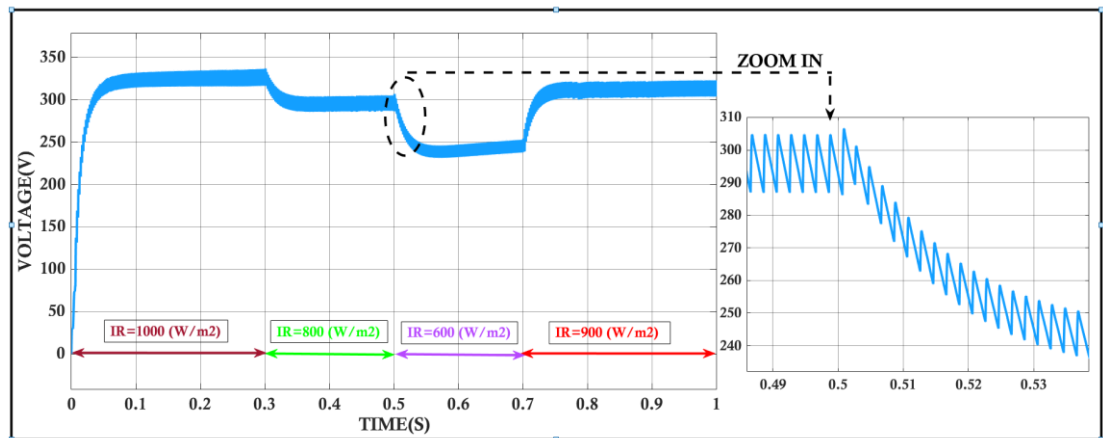


Figure (IV.15): Voltage Simulation Result

Figure IV.15 illustrates the voltage response of an Incremental Conductance-based MPPT system under changing irradiance conditions. The primary graph depicts a rapid increase in voltage followed by stabilization near 330 V, with discrete stepwise declines corresponding to decreasing irradiance. The inset provides a closer examination of transient voltage fluctuations during these transitions.

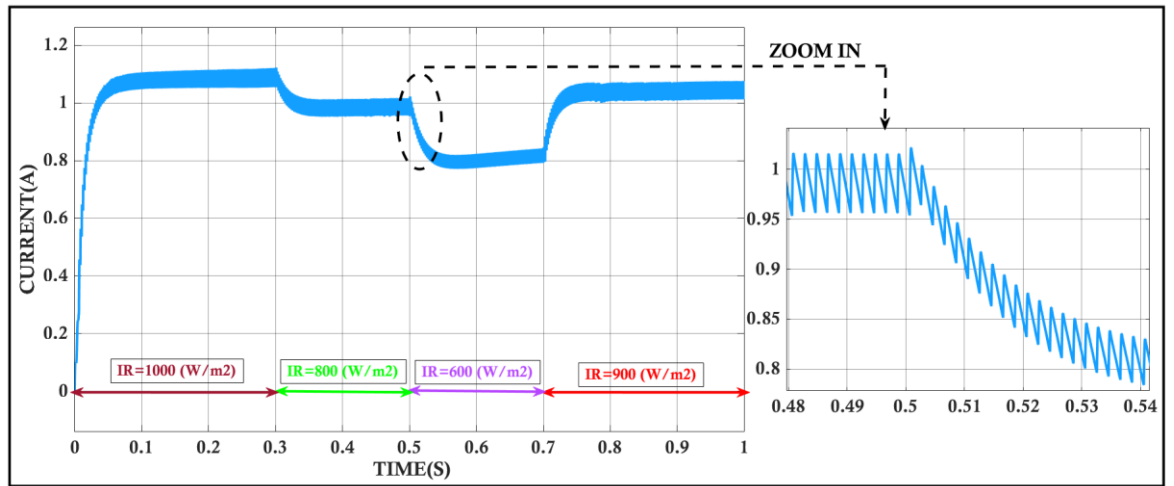


Figure (IV.16): Current Simulation Result

The Figure (IV.16) demonstrates the current response of an MPPT system using the Incremental Conductance algorithm under varying irradiance conditions. The main plot shows the current stabilizing around 1.1A initially, with stepwise decreases as the irradiance drops. The zoomed-in view captures transient fluctuations during an irradiance change.

IV.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 (IV.17) 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.

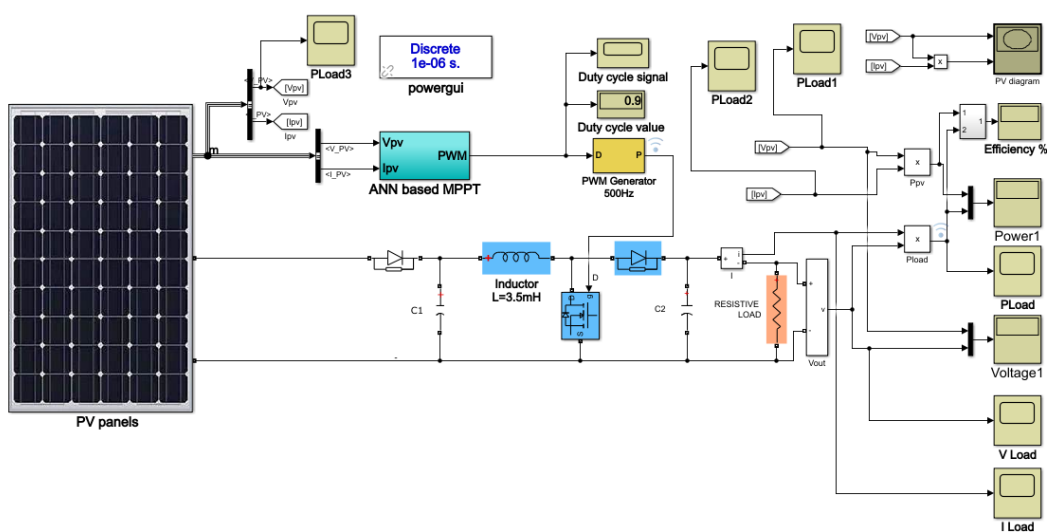


Figure (IV.17): Scheme of System Simulation With ANN

a) Constant Irradiance (1000 W/m²) :

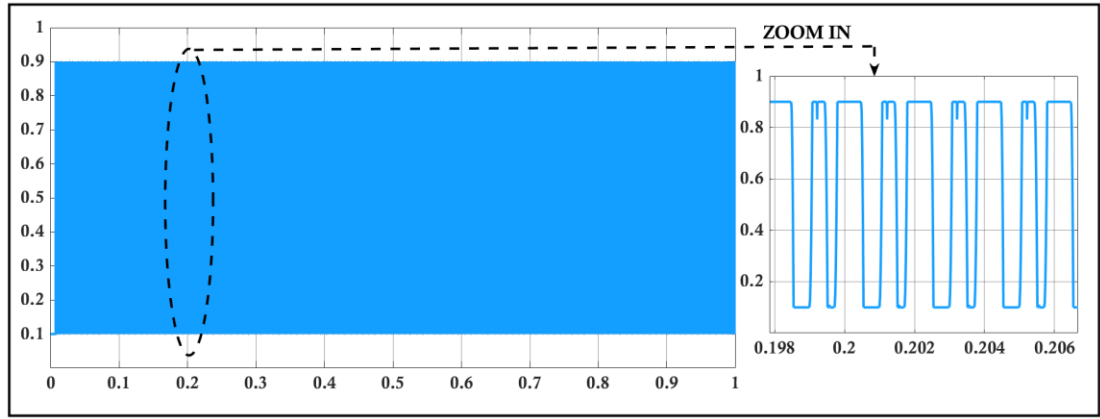


Figure (IV.18): Duty Cycle Simulation Result

The Figure (IV.18) 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.

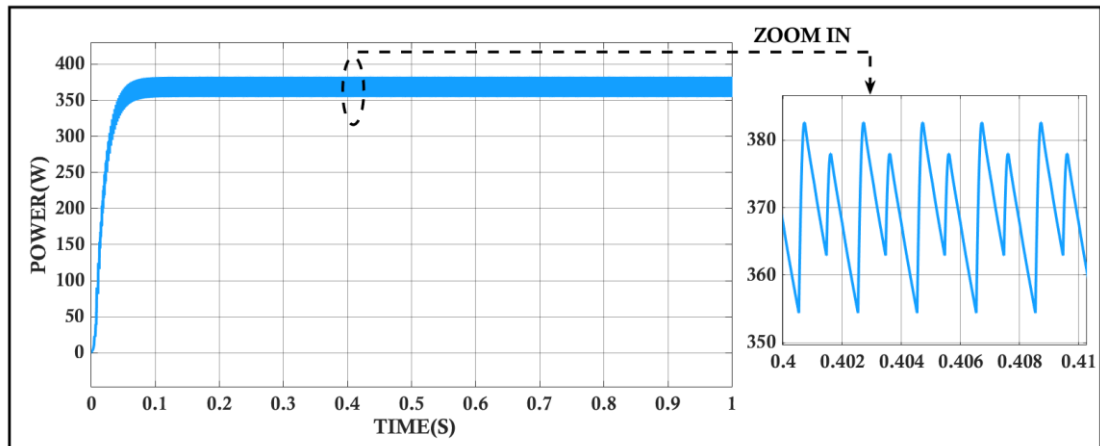


Figure (IV.19): Power Simulation Result

Figure IV.19 illustrates the power stabilization characteristics of a maximum power point tracking (MPPT) system controlled by an artificial neural network (ANN) algorithm. The primary graph shows a swift increase in power reaching a steady level near 380 W, indicating the system's operational efficiency. A magnified section reveals periodic oscillations, which represent the ANN's continual fine-tuning to sustain optimal power output. This observation highlights the ANN algorithm's ability to dynamically and accurately track the maximum power point.

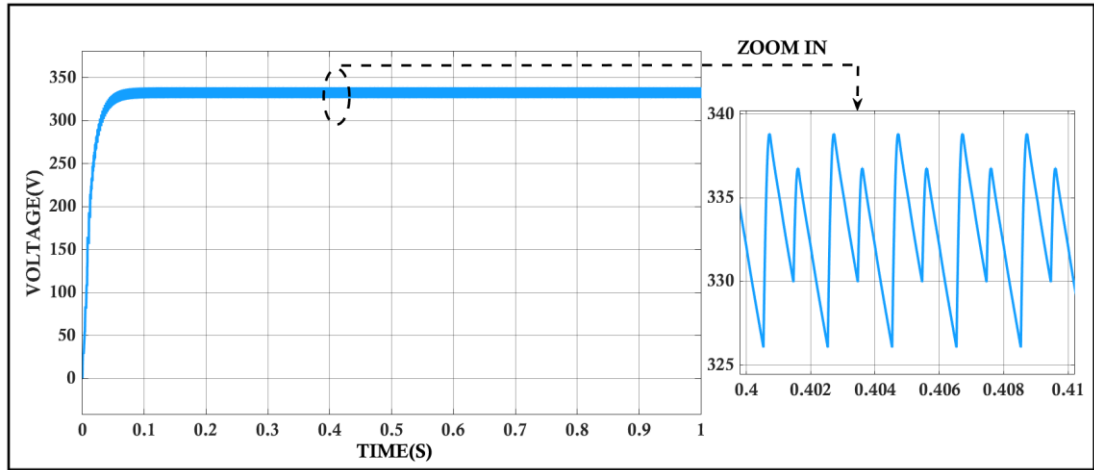


Figure (IV.20): Voltage Simulation Result

The Figure (IV.20) illustrates the voltage behavior of an ANN-based MPPT system. The main plot shows a quick rise and stabilization around 335V, while the zoomed-in view captures small fluctuations.

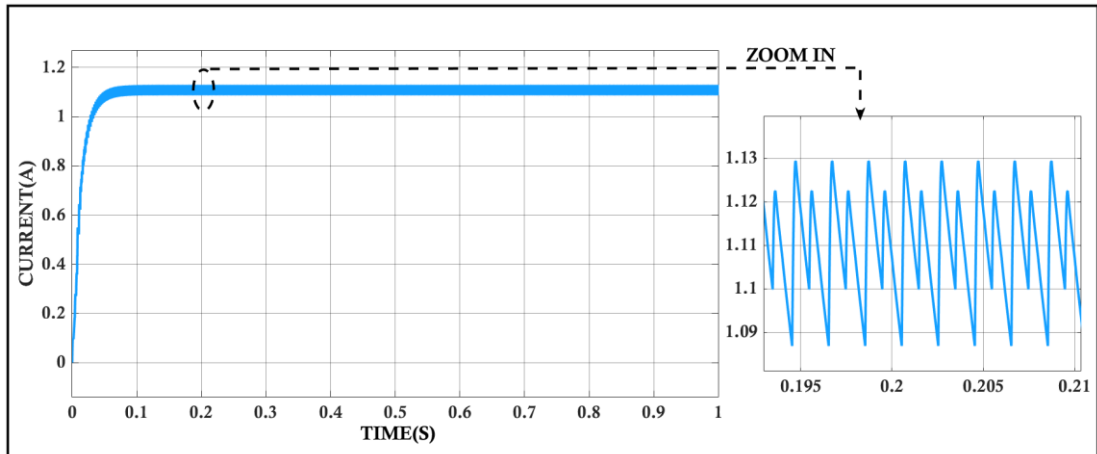


Figure (IV.21): Current Simulation Result

The Figure (IV.21) shows the current stabilization of an ANN-based MPPT system. The main plot displays a rapid rise in current, stabilizing around 1.1A. The zoomed-in view highlights small fluctuations.

b) Variable Irradiances (1000, 800, 600, 900 W/m²) :

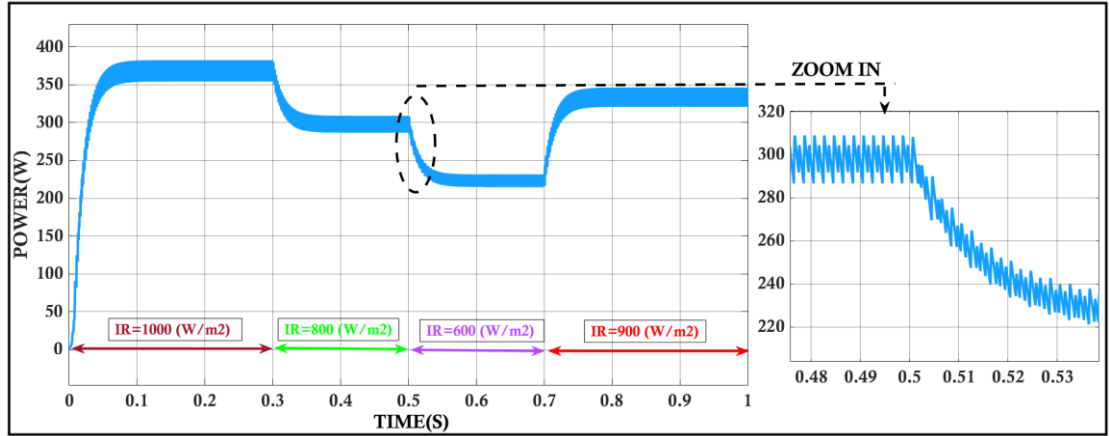


Figure (IV.22): Power Simulation Result

Figure IV.22 illustrates the response of the ANN-based MPPT system in regulating power output under fluctuating irradiance levels. The primary graph indicates that the power output initially stabilizes near 350W, followed by discrete reductions corresponding to decreases in irradiance. The inset provides a detailed view of the transient variations occurring during changes in irradiance..

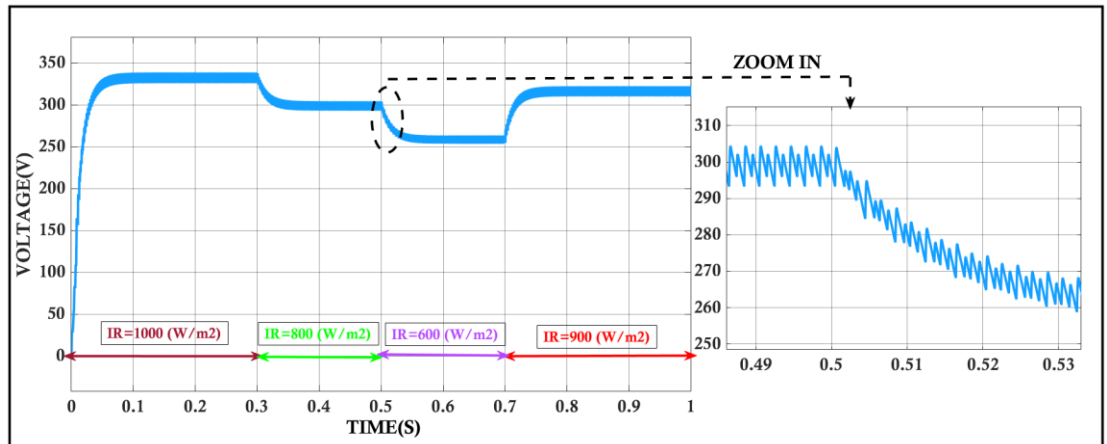


Figure (IV.23): Voltage Simulation Result

Figure IV.23 depicts the voltage response of the ANN-based MPPT system under varying levels of solar irradiance. The primary graph indicates that the voltage remains approximately stable near 330 V, decreasing incrementally as irradiance diminishes. The inset provides a closer examination of transient voltage fluctuations. These observations highlight the algorithm's ability to adapt dynamically to real-time variations in irradiance, thereby maintaining effective system performance.

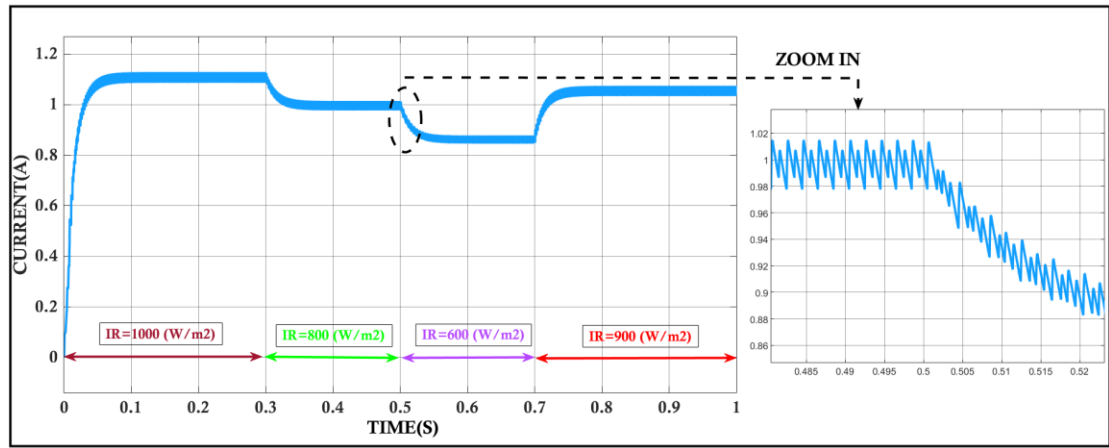


Figure (IV.24): Current Simulation Result

Figure IV.24 illustrates the current response of an ANN-based MPPT system subjected to varying irradiance levels. The primary graph indicates that the current initially stabilizes near 1.1 A, followed by stepwise declines corresponding to reductions in irradiance. The inset provides a detailed view of transient fluctuations occurring during changes in irradiance.

IV.3.4 Fuzzy Logic Controller (FLC) algorithm:

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

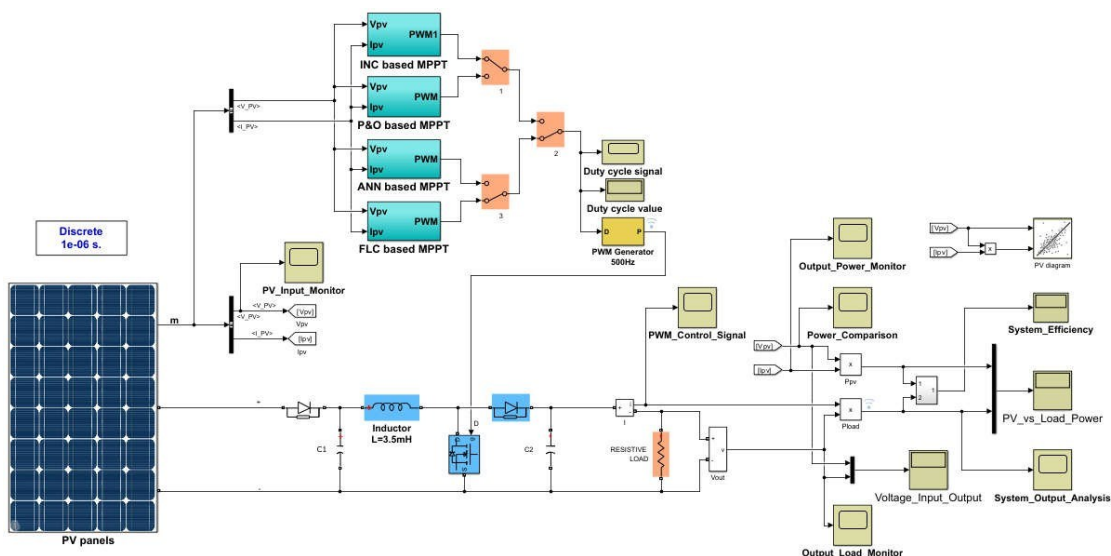
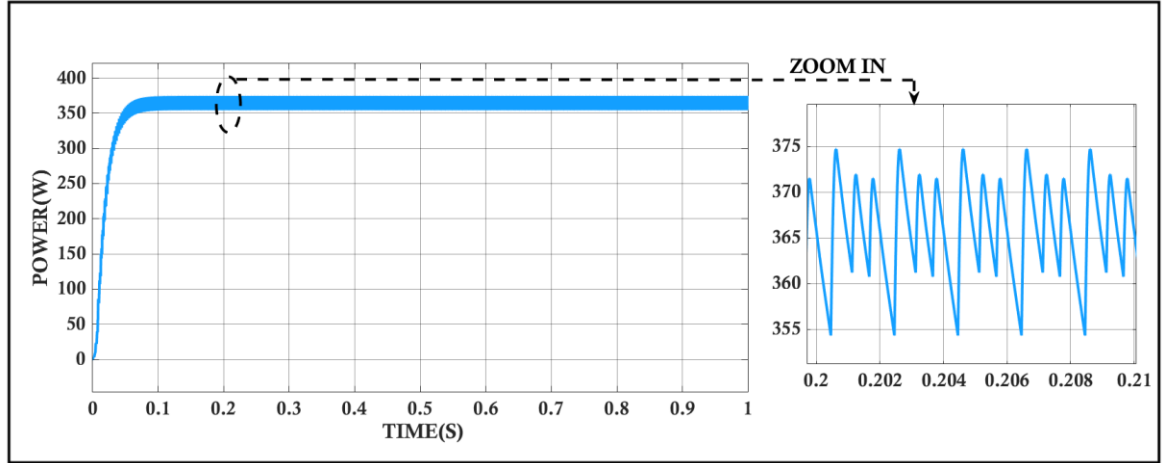
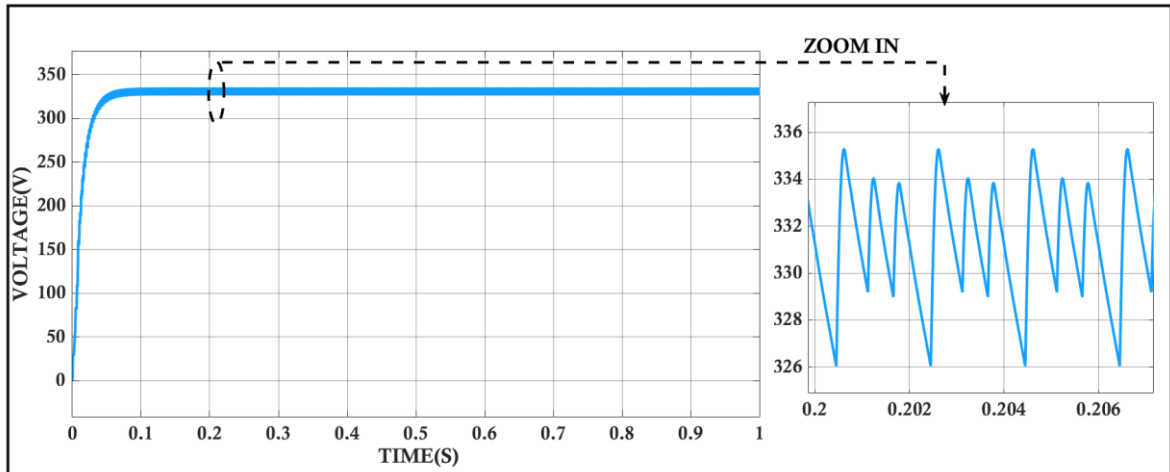


Figure (IV.25): Schematic simulation system with FLC

a)- Constant irradiance (1000 W/m²) and constant temperature (25°C)**Figure (IV.26): Power simulation result versus time for FLC in constant irradiance**

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

**Figure (IV.27): Voltage simulation result versus time for FLC in constant irradiance**

The figure represents the voltage behavior of an FLC-based MPPT system under constant irradiance conditions. The curve shows a rapid rise in voltage, quickly stabilizing around a specific value (approximately 335V). This indicates the system's ability to adapt efficiently and reach optimal performance under stable environ conditions. While the zoomed-in views the mental magnified section reveals minor fluctuations after stabilization, reflecting

the system's continuous fine-tuning to maintain maximum power point tracking with high precision despite minor load or condition changes.

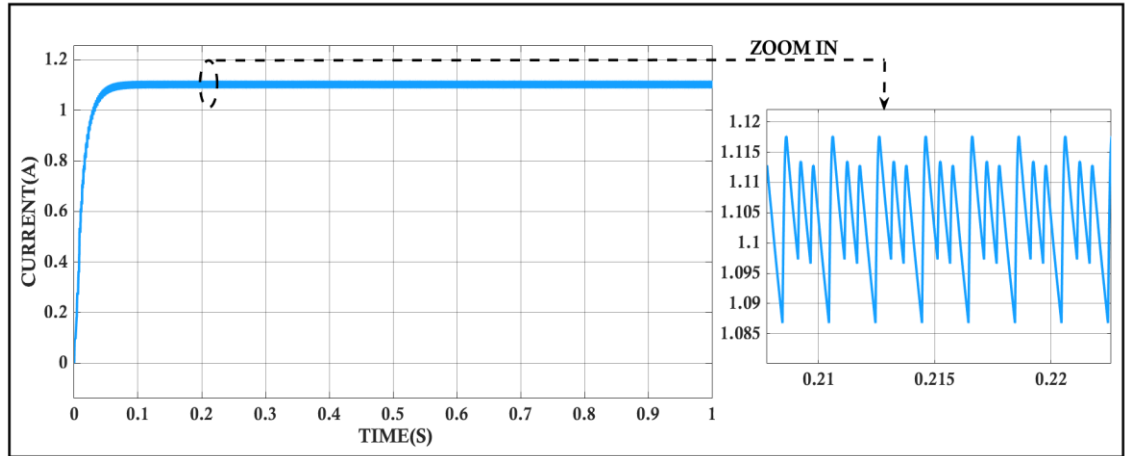


Figure (IV.28): Current simulation result versus time for ANN in constant irradiance

The Figure (IV.28) illustrates the current stabilization of an FLC-based MPPT system. The main plot shows a rapid rise in current, stabilizing around 1.1 A. The zoomed-in view highlights small fluctuations near the stabilization point. This behavior reflects the efficiency of the FLC system under constant irradiance conditions, with minor deviations due to its rule-based nature.

b)- Variable irradiances (1000, 800, 600, 900 W/m²) and constant temperature (25°C)

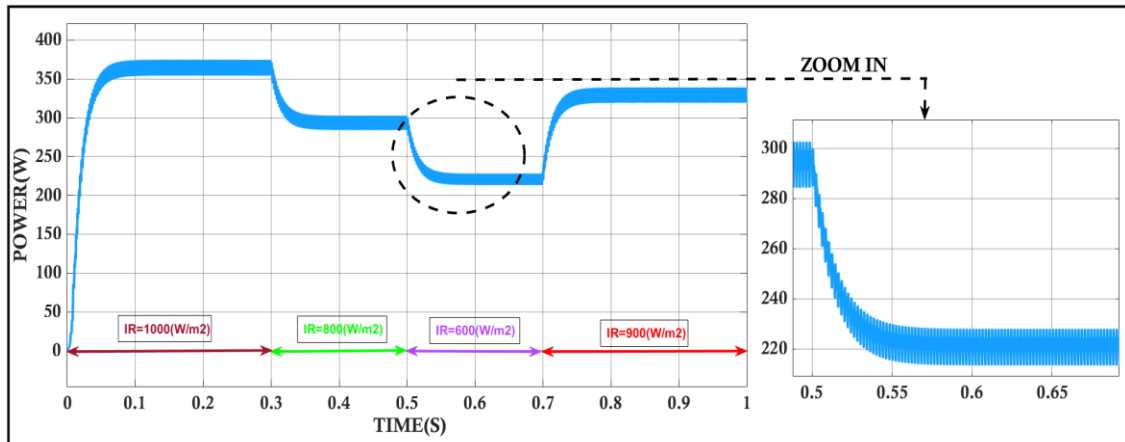


Figure (IV.29): Power simulation result versus time for FLC in variable irradiances

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

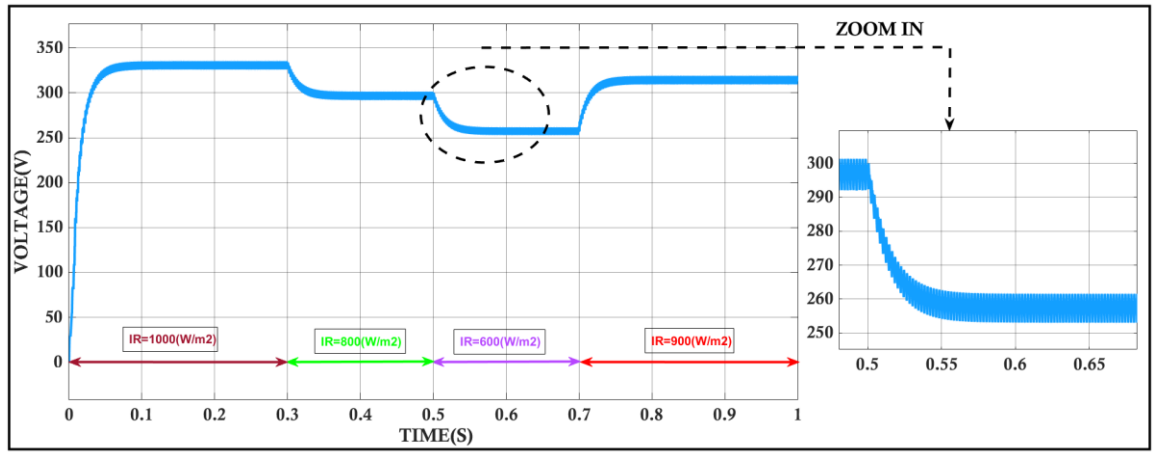


Figure (IV.30): Voltage simulation result versus time for FLC in variable irradiances

The Figure (IV.30) illustrates the FLC-based MPPT system's voltage response to varying irradiance. The main plot shows the voltage stabilizing around 330V and stepping down to approximately 250-270V with decreasing irradiance. The zoomed-in view reveals minor transient fluctuations during adaptation. Each stabilization period after irradiance changes takes approximately 0.02 to 0.05 seconds. This demonstrates the FLC algorithm's ability to efficiently adapt to dynamic solar irradiance changes while maintaining stable performance.

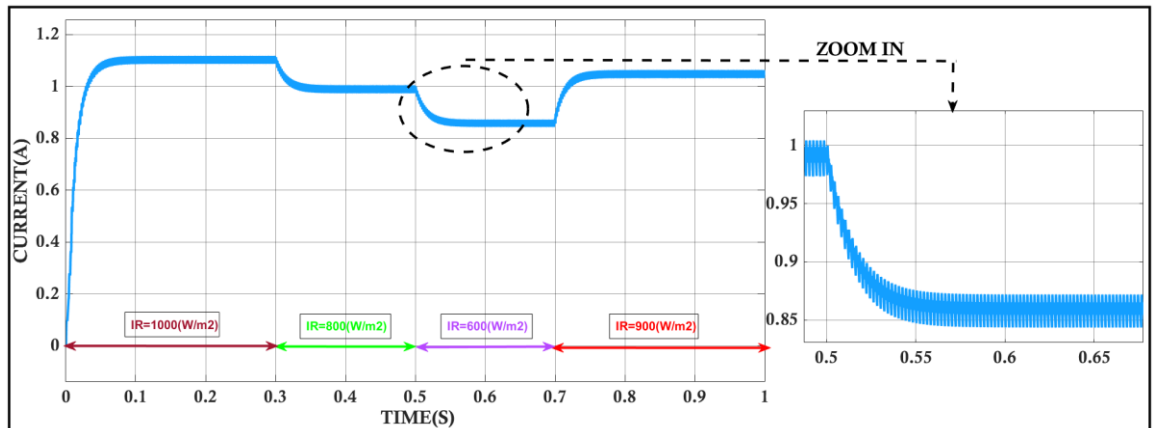


Figure (IV.31): Current simulation result versus time for FLC in variable irradiances

The figure (IV.31) depicts the current response of an FLC-based MPPT system under fluctuating irradiance levels. Initially, the current stabilizes at approximately 1.1A, showing steady behaviour. As irradiance decreases, the current exhibits stepwise reductions, reaching around 0.8A during lower irradiance periods. The zoomed-in section highlights transient fluctuations, with minor oscillations of about $\pm 0.05A$, reflecting the system's dynamic adaptation to rapid changes in irradiance.

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

IV.4.1 Constant Irradiance (1000 W/m^2)

The following figures compare the power, current and voltage in constant irradiance outputs of four MPPT algorithms: Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Network (ANN) and Fuzzy Logic Control (FLC).

a)- Analysis of Voltage Tracking Performance

The provided graph compares the voltage tracking performance of four different control strategies over time. The strategies are:

1. V (P&O) : Perturb and Observe method.
2. V (INC) : Incremental Conductance method.
3. V (ANN) : Artificial Neural Network-based method.
4. V (FLC) : Fuzzy Logic Control-based method.

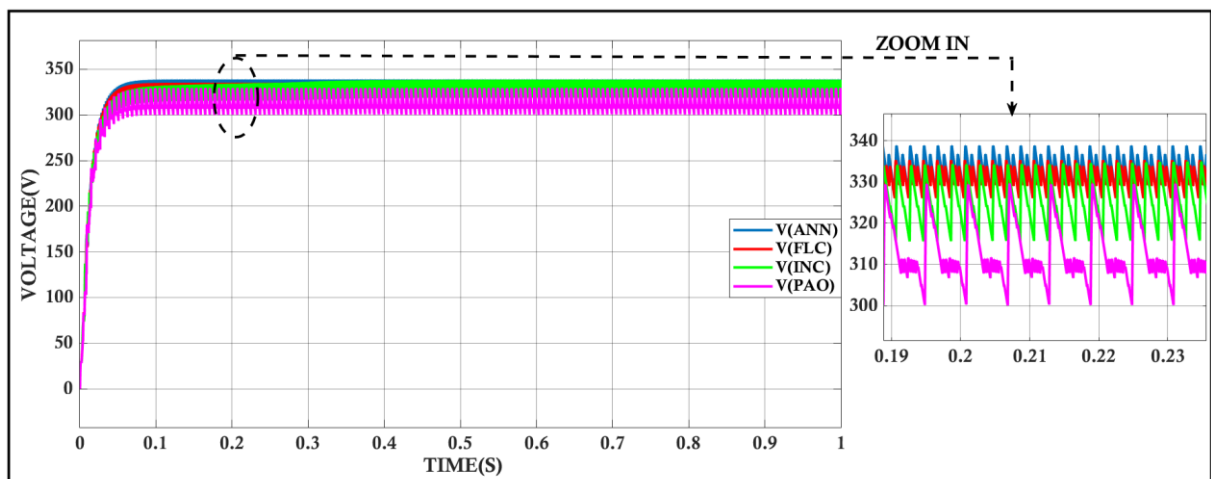


Figure (IV.32): Voltage simulation result versus time in constant irradiance of four MPPT algorithms

IV.4.2 Main Graph Analysis

- Time Range: The main graph spans from 0 to 1 second.
- Voltage Range: The voltage values range from approximately 0 V to 350 V.
- Initial Transient Behavior :
 - All methods start at 0 V and rapidly increase their voltage output within the first 0.1 seconds.
 - The V (FLC) method (red line) reaches its peak voltage slightly faster than the others, indicating a quicker response time.
 - The V (P&O) method (pink line) shows a smooth and steady increase in voltage.

-The V (INC) method (green line) and V (ANN) method (blue line) also show rapid increases but with slight oscillations compared to V (P&O) .

- Steady-State Performance :

-After approximately 0.1 seconds, all methods stabilize around a voltage level of 330 V .

-The V (P&O) method maintains a very stable voltage output with minimal fluctuations.

-The V (INC) and V (ANN) methods exhibit small oscillations around the steady-state value.

-The V (FLC) method shows a slightly higher steady-state voltage compared to the others, reaching approximately 340 V .

IV.4.3 Zoomed-In Section Analysis

-Time Range : The zoomed-in section focuses on the interval from 0.19 to 0.23 seconds.

-Voltage Range : The voltage values in this section range from approximately 300V to 340V.

- Detailed Observations :

-The V (FLC) method consistently achieves the highest voltage output, peaking at 340 V .

-The V (P&O) method shows significant fluctuations, dropping as low as 300 V and recovering to around 310 V .

-The V (INC) method and V (ANN) method maintain relatively stable outputs around 330 V , with minor oscillations.

IV.4.4 Comparison of Methods

Table (IV.2): Comparison the voltage between the four methods in constant irradiance

Method	Initial Response	Steady-State Voltage	Fluctuations	Peak Voltage
V (P&O)	Smooth, moderate	~330 V	Minimal	~330 V
V (INC)	Rapid, with oscillations	~330 V	Moderate	~330 V
V (ANN)	Rapid, with oscillations	~330 V	Moderate	~330 V
V (FLC)	Fastest	~340 V	Slight	~340 V

IV.4.5 Key Findings

- Response Time : The V (FLC) method has the fastest initial response, reaching its peak voltage quickest.
- Steady-State Stability : The V (P&O) method demonstrates the most stable steady-state performance with minimal fluctuations.
- Peak Voltage Output : The V (FLC) method achieves the highest peak voltage output, reaching 340 V .
- Oscillations : Both the V (INC) and V (ANN) methods exhibit more noticeable oscillations compared to V (P&O) and V (FLC) .

Conclusion

The V (FLC) method outperforms the others in terms of peak voltage and initial response speed. However, it shows slight fluctuations in the steady state. The V (P&O) method provides the most stable voltage output with minimal fluctuations, making it suitable for applications requiring high reliability. The V (INC) and V (ANN) methods offer good performance but with some oscillations that may affect system stability under certain conditions.

Final Recommendation

For applications prioritizing peak voltage and fast response, the V (FLC) method is recommended. For applications requiring highly stable voltage output, the V (P&O) method is the best choice.

b)- Analysis of Current Tracking Performance

The provided graph compares the current tracking performance of four different control strategies over time. The strategies are:

1. I (P&O) : Perturb and Observe method.
2. I (INC) : Incremental Conductance method.
3. I (ANN) : Artificial Neural Network-based method.
4. I (FLC) : Fuzzy Logic Control-based method.

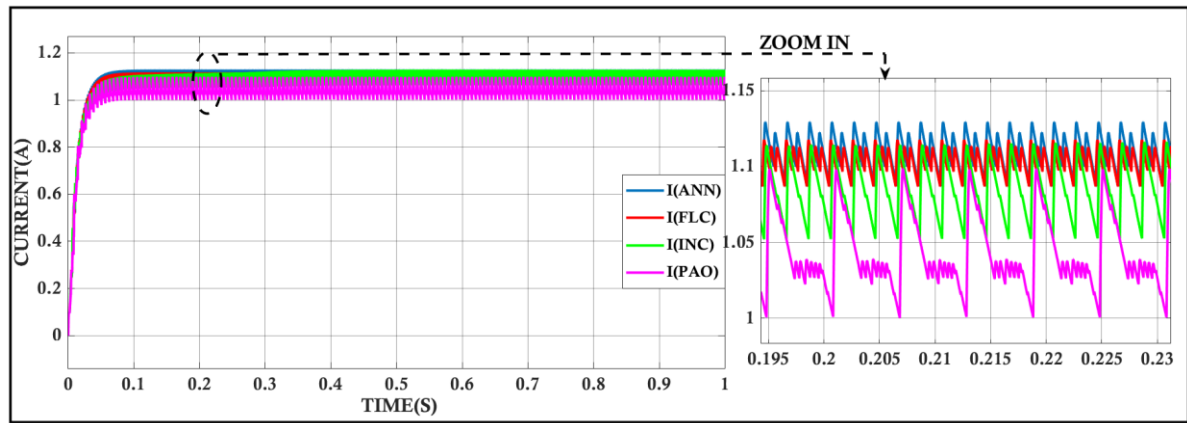


Figure (IV.33): Current simulation result versus time in constant irradiance of four MPPT algorithms

Main Graph Analysis

- Time Range : The main graph spans from 0 to 1 second.
- Current Range : The current values range from approximately 0 A to 1.2 A.
- Initial Transient Behavior :
 - All methods start at 0 A and rapidly increase their current output within the first 0.1 seconds.
 - The I (FLC) method (red line) reaches its peak current slightly faster than the others, indicating a quicker response time.
 - The I (P&O) method (pink line) shows a smooth and steady increase in current.
 - The I (INC) method (green line) and I (ANN) method (blue line) also show rapid increases but with slight oscillations compared to I (P&O) .
- Steady-State Performance :
 - After approximately 0.1 seconds, all methods stabilize around a current level of 1.1A .
 - The I (P&O) method maintains a very stable current output with minimal fluctuations.
 - The I (INC) and I (ANN) methods exhibit small oscillations around the steady-state value.
 - The I (FLC) method shows a slightly higher steady-state current compared to the others, reaching approximately 1.12 A .

Zoomed-In Section Analysis

- Time Range : The zoomed-in section focuses on the interval from 0.195 to 0.23 seconds.

-Current Range : The current values in this section range from approximately 1 A to 1.12A.

- Detailed Observations :

-The I (FLC) method consistently achieves the highest current output, peaking at 1.12 A .

-The I (P&O) method shows significant fluctuations, dropping as low as 1 A and recovering to around 1.02 A .

-The I (INC) method and I (ANN) method maintain relatively stable outputs around 1.1 A , with minor oscillations.

Comparison of Methods

Table (IV.3): Comparison the current between the four methods in constant irradiance

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

Key Findings

-Response Time : The I (FLC) method has the fastest initial response, reaching its peak current quickest.

-Steady-State Stability : The I (P&O) method demonstrates the most stable steady-state performance with minimal fluctuations.

-Peak Current Output : The I (FLC) method achieves the highest peak current output, reaching 1.12 A .

-Oscillations : Both the I (INC) and I (ANN) methods exhibit more noticeable oscillations compared to I (P&O) and I (FLC) .

Conclusion

The I (FLC) method outperforms the others in terms of peak current and initial response speed. However, it shows slight fluctuations in the steady state. The I (P&O) method provides the most stable current output with minimal fluctuations, making it suitable for applications

requiring high reliability. The I (INC) and I (ANN) methods offer good performance but with some oscillations that may affect system stability under certain conditions.

Final Recommendation

For applications prioritizing peak current and fast response, the I (FLC) method is recommended. For applications requiring highly stable current output, the I (P&O) method is the best choice.

c)- Analysis of Power Tracking Performance

The provided graph compares the power tracking performance of four different control strategies over time. The strategies are:

1. P (P&O) : Perturb and Observe method.
2. P (INC) : Incremental Conductance method.
3. P (ANN) : Artificial Neural Network-based method.
4. P (FLC) : Fuzzy Logic Control-based method

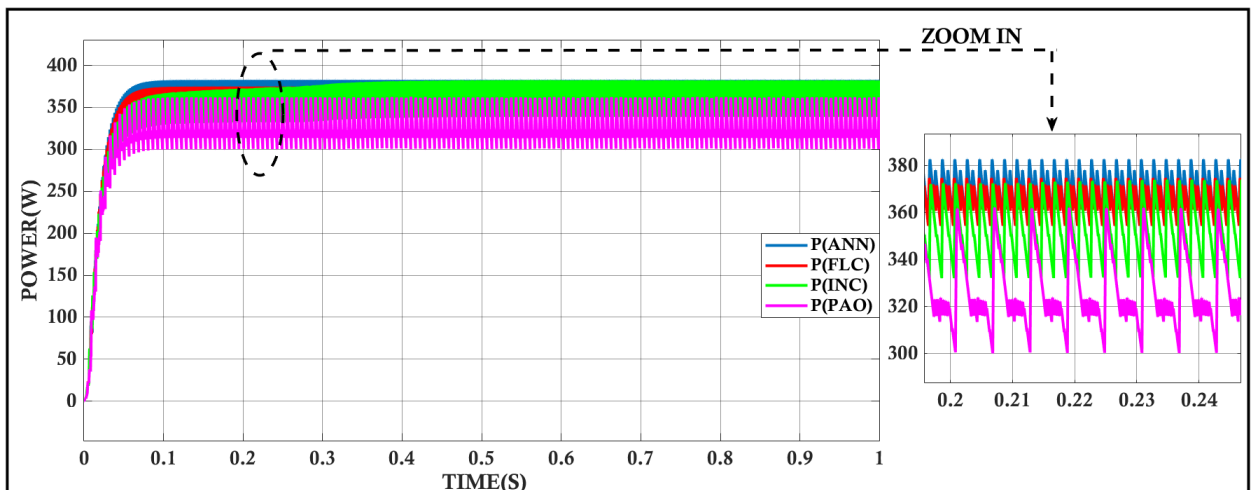


Figure (IV.34): Power simulation result versus time in constant irradiance of four MPPT algorithms

Main Graph Analysis

- Time Range : The main graph spans from 0 to 1 second.
- Power Range : The power values range from approximately 0 W to 400 W.
- Initial Transient Behavior :
 - All methods start at 0 W and rapidly increase their power output within the first 0.1 seconds.
 - The P (FLC) method (red line) reaches its peak power slightly faster than the others, indicating a quicker response time.
 - The P (P&O) method (pink line) shows a smooth and steady increase in power.

-The P (INC) method (greenline) and P (ANN) method (blue line) also show rapid increases but with slight oscillations compared to P (P&O) .

- Steady-State Performance :

-After approximately 0.1 seconds, all methods stabilize around a power level of 350W .

-The P (P&O) method maintains a very stable power output with minimal fluctuations.

-The P (INC) and P (ANN) methods exhibit small oscillations around the steady- state value.

-The P (FLC) method shows a slightly higher steady-state power level compared to the others, reaching approximately 380 W.

Zoomed-In Section Analysis

-Time Range : The zoomed-in section focuses on the interval from 0.14 to 0.15 seconds.

-Power Range : The power values in this section range from approximately 300 W to 380W.

- Detailed Observations :

-The P (FLC) method consistently achieves the highest power output, peaking at 380 W .

-The P (P&O) method shows significant fluctuations, dropping as low as 300 W and recovering to around 320 W .

-The P (INC) method and P (ANN) method maintain relatively stable outputs around 360 W , with minor oscillations.

Comparison of Methods

Table (IV.4): Comparison the power between the four methods in constant irradiance

Method	Initial Response	Steady-State Power	Fluctuations	Peak Power
P (P&O)	Smooth, moderate	~350 W	Minimal	~350 W
P (INC)	Rapid, with oscillations	~350 W	Moderate	~350 W
P (ANN)	Rapid, with oscillations	~350 W	Moderate	~350 W
P (FLC)	Fastest	~380 W	Slight	~380 W

Key Findings

- Response Time : The P (FLC) method has the fastest initial response, reaching its peak power quickest.
- Steady-State Stability : The P (P&O) method demonstrates the most stable steady-state performance with minimal fluctuations.
- Peak Power Output : The P (FLC) method achieves the highest peak power output, reaching 380 W .
- Oscillations : Both the P (INC) and P (ANN) methods exhibit more noticeable oscillations compared to P (P&O) and P (FLC).

Summary

The P (FLC) method outperforms the others in terms of peak power output and initial response speed. However, it shows slight fluctuations in the steady state. The P (P&O) method provides the most stable power output with minimal fluctuations, making it suitable for applications requiring high reliability. The P (INC) and P (ANN) methods offer good performance but with some oscillations that may affect system stability under certain conditions.

Final Recommendation

For applications prioritizing peak power and fast response, the P (FLC) method is recommended. For applications requiring highly stable power output, the P (P&O) method is the best choice.

III.4.1 Variable Irradiances (1000, 800, 600, 900 W/m²)

The following figures compare the power, current and voltage in variable irradiances outputs of four MPPT algorithms: Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Network (ANN) and Fuzzy Logic Control (FLC).

a)- Analysis of Voltage Tracking Performance Under Varying Irradiance Conditions

The provided graph compares the voltage tracking performance of four different control strategies under varying irradiance (IR) conditions. The strategies are:

1. V (P&O) : Perturb and Observe method.

2. V (INC) : Incremental Conductance method.
3. V (ANN) : Artificial Neural Network-based method.
4. V (FLC) : Fuzzy Logic Control-based method.

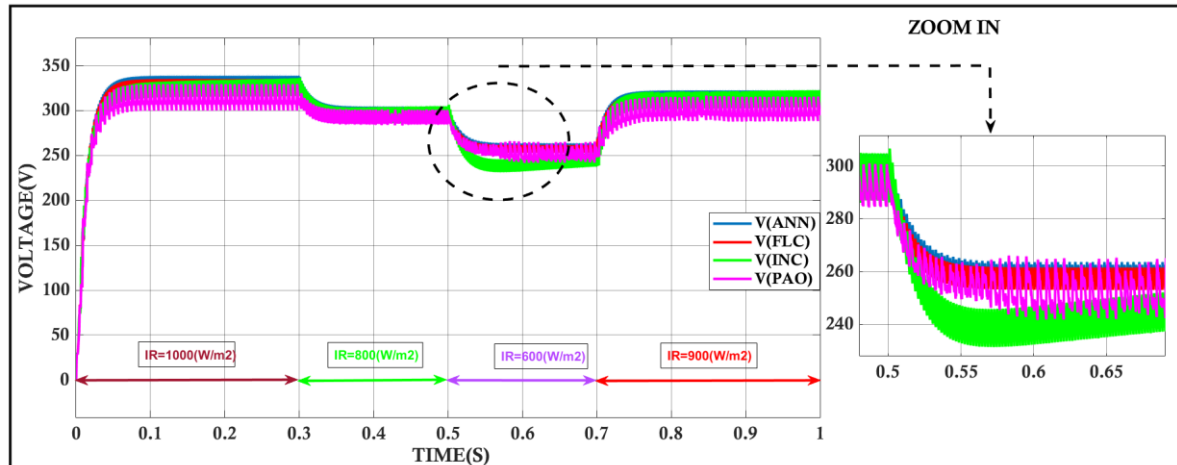


Figure (IV.35): Voltage simulation result versus time in variable irradiance of four MPPT algorithms

Main Graph Analysis

- Time Range : The main graph spans from 0 to 1 second.
- Voltage Range : The voltage values range from approximately 0 V to 350 V.
- Irradiance Levels :
 - IR = 1000 W/m² : From 0 to 0.3 seconds.
 - IR = 800 W/m² : From 0.3 to 0.5 seconds.
 - IR = 600 W/m² : From 0.5 to 0.7 seconds.
 - IR = 900 W/m² : From 0.7 to 1 second.

Behavior Under Different Irradiance Levels

- 1-Initial Transient Behavior (IR = 1000 W/m²) :
 - All methods start at 0 V and rapidly increase their voltage output within the first 0.1 seconds.
 - The V (FLC) method (red line) reaches its peak voltage slightly faster than the others, indicating a quicker response time.
 - The V (P&O) method (pink line) shows a smooth and steady increase in voltage.
 - The V (INC) method (green line) and V (ANN) method (blue line) also show rapid increases but with slight oscillations compared to V (P&O) .
- 2-Steady-State Performance at IR = 1000 W/m² :
 - After approximately 0.1 seconds, all methods stabilize around a voltage level of 330 V .

- The V (P&O) method maintains a very stable voltage output with minimal fluctuations.
- The V (INC) and V (ANN) methods exhibit small oscillations around the steady-state value.
- The V (FLC) method shows a slightly higher steady-state voltage compared to the others, reaching approximately 340 V .

3-Response to Decreasing Irradiance :

- As the irradiance decreases from 1000 W/m² to 800 W/m² , all methods show a decrease in voltage.
- The V (FLC) method demonstrates the fastest response to the change in irradiance, maintaining a smoother transition compared to the other methods.
- The V (P&O) method shows a gradual decrease in voltage but with some overshoot and undershoot during the transition.
- The V (INC) and V (ANN) methods exhibit more noticeable oscillations during the transition.

4-Steady-State Performance at Lower Irradiances :

- At IR = 800 W/m² , the steady-state voltage for all methods is around 300V.
- At IR = 600 W/m² , the steady-state voltage drops to approximately 250V.
- At IR = 900 W/m² , the steady-state voltage further increases to around 200V.
- Throughout these transitions, the V (FLC) method consistently shows the least fluctuation and the fastest adaptation to the new irradiance levels.

Zoomed-In Section Analysis

-Time Range : The zoomed-in section focuses on the interval from 0.5 to 0.7 seconds (transition from IR = 800 W/m² to IR = 600 W/m²).

-Voltage Range : The voltage values in this section range from approximately 200 V to 300V.

• Detailed Observations :

- The V (FLC) method (pink dashed line) shows the smoothest transition, maintaining a consistent voltage drop without significant overshoot or undershoot.
- The V (P&O) method (blue solid line) exhibits significant fluctuations, dropping sharply and recovering slowly.
- The V (INC) method (red dashed line) and V (ANN) method (green solid line) show more pronounced oscillations during the transition.

Comparison of Methods

Table (IV.5): Comparison the voltage between the four methods in variable irradiances

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

(FLC) method has the fastest initial response, reaching its peak voltage quickest.

-Adaptation to Changing Irradiance : The V (FLC) method demonstrates the fastest and most stable adaptation to decreasing irradiance levels, showing minimal overshoot and undershoot.

-Steady-State Stability : The V (P&O) method provides the most stable steady-state performance with minimal fluctuations under constant irradiance.

-Oscillations : Both the V (INC) and V (ANN) methods exhibit more noticeable oscillations compared to V (P&O) and V (FLC) , especially during transitions.

Summary

The V(FLC) method outperforms the others in terms of adaptability to changing irradiance conditions, achieving the fastest and smoothest transitions with minimal fluctuations. However, under constant irradiance, the V(P&O) method provides the most stable steady-state performance. The V(INC) and V(ANN) methods offer good performance

but with more oscillations during transitions.

Final Recommendation

For applications requiring robust performance under dynamic irradiance conditions, the V(FLC) method is recommended due to its fast adaptation and stability. For applications operating under constant irradiance, the V(P&O) method is the best choice for its steady-state stability.

b)- Analysis of Current Tracking Performance Under Varying Irradiance Conditions

The provided graph compares the current tracking performance of four different control strategies under varying irradiance (IR) conditions. The strategies are:

1. **I (P&O)** : Perturb and Observe method.
2. **I (INC)** : Incremental Conductance method.
3. **I (ANN)** : Artificial Neural Network-based method.
4. **I (FLC)** : Fuzzy Logic Control-based method.

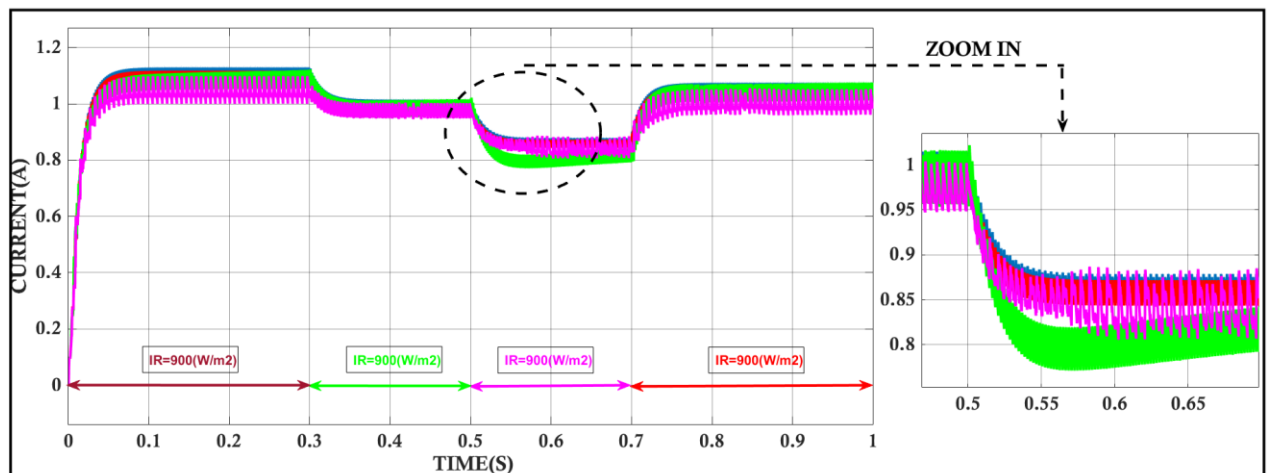


Figure (IV.36): Current simulation result versus time in variable irradiance of four MPPT algorithms

Main Graph Analysis

- Time Range** : The main graph spans from 0 to 1 second.
- Current Range** : The current values range from approximately 0 A to 1.2 A.
- Irradiance Levels** :

- IR = 1000 W/m² : From 0 to 0.3 seconds.
- IR = 800 W/m² : From 0.3 to 0.5 seconds.
- IR = 600 W/m² : From 0.5 to 0.7 seconds.
- IR = 900 W/m² : From 0.7 to 1 second.

Behavior Under Different Irradiance Levels

1-Initial Transient Behavior ($IR = 1000 \text{ W/m}^2$) :

- All methods start at 0 A and rapidly increase their current output within the first 0.1 seconds.
- The I (FLC) method (red line) reaches its peak current slightly faster than the others, indicating a quicker response time.
- The I (P&O) method (pink line) shows a smooth and steady increase in current.
- The I (INC) method (green line) and I (ANN) method (blue line) also show rapid increases but with slight oscillations compared to I (P&O) .

2-Steady-State Performance at $IR = 1000 \text{ W/m}^2$:

- After approximately 0.1 seconds, all methods stabilize around a current level of 1.1A .
- The I (P&O) method maintains a very stable current output with minimal fluctuations.
- The I (INC) and I (ANN) methods exhibit small oscillations around the steady-state value.
- The I (FLC) method shows a slightly higher steady-state current compared to the others, reaching approximately 1.12 A .

3-Response to Decreasing Irradiance :

- As the irradiance decreases from 1000 W/m^2 to 800 W/m^2 , all methods show a decrease in current.
- The I (FLC) method demonstrates the fastest response to the change in irradiance, maintaining a smoother transition compared to the other methods.
- The I (P&O) method shows a gradual decrease in current but with some overshoot and undershoot during the transition.
- The I (INC) and I (ANN) methods exhibit more noticeable oscillations during the transition.

4-Steady-State Performance at Lower Irradiances :

- At $IR = 800 \text{ W/m}^2$, the steady-state current for all methods is around 1 A .
- At $IR = 600 \text{ W/m}^2$, the steady-state current drops to approximately 0.8 A .
- At $IR = 900 \text{ W/m}^2$, the steady-state current further increases to around 1.1 A .
- Throughout these transitions, the I (FLC) method consistently shows the least fluctuation and the fastest adaptation to the new irradiance levels.

Zoomed-In Section Analysis

- Time Range : The zoomed-in section focuses on the interval from 0.5 to 0.7 seconds (transition from $IR = 800 \text{ W/m}^2$ to $IR = 600 \text{ W/m}^2$).

-Current Range : The current values in this section range from approximately 0.6 A to 1 A.

• **Detailed Observations :**

-The I (FLC) method shows the smoothest transition, maintaining a consistent current drop without significant overshoot or undershoot.

-The I (P&O) method exhibits significant fluctuations, dropping sharply and recovering slowly.

-The I (INC) method and I (ANN) method show more pronounced oscillations during the transition.

Comparison of Methods

Table (IV.6): Comparison the current between the four methods in variable irradiances

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

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method has the fastest initial response, reaching its peak current quickest.

-Adaptation to Changing Irradiance : The I (FLC) method demonstrates the fastest and most stable adaptation to decreasing irradiance levels, showing minimal overshoot and undershoot.

-Steady-State Stability : The I (P&O) method provides the most stable steady-state performance with minimal fluctuations under constant irradiance.

-Oscillations : Both the I (INC) and I (ANN) methods exhibit more noticeable oscillations compared to I (P&O) and I (FLC) , especially during transitions.

Summary

The I (FLC) method outperforms the others in terms of adaptability to changing irradiance conditions, achieving the fastest and smoothest transitions with minimal fluctuations. However, under constant irradiance, the I (P&O) method provides the most stable steady-state performance. The I (INC) and I (ANN) methods offer good performance but with more oscillations during transitions.

Final Recommendation

For applications requiring robust performance under dynamic irradiance conditions, the I(FLC) method is recommended due to its fast adaptation and stability. For applications operating under constant irradiance, the I(P&O) method is the best choice for its steady-state stability.

Comparison of efficiency between algorithms (P&O, INC, ANN and FLC) Constant Irradiance (1000 W/m²)

Table (IV.7): Table of efficiency in constant irradiance

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

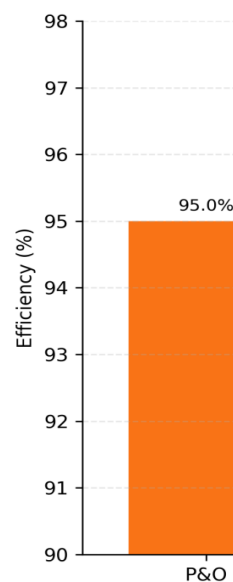


Figure (IV.37): Chart of efficiency in constant irradiance

The table (IV.7) and curve (IV.37) provide efficiency (η) values for four Maximum Power Point Tracking (MPPT) algorithms under constant irradiance (1000W/m²):

Perturb and Observe (P&O), Incremental Conductance (INC), Artificial

Neural Network (ANN) and Fuzzy Logic Controller (FLC)
1.Key Observations

- Highest Efficiency : The Artificial Neural Network (ANN) algorithm achieves the highest efficiency at 96.63% .
- Ranking by Efficiency : ANN > INC > P&O > FLC.
- Lowest Efficiency : The Fuzzy Logic Controller (FLC) algorithm has the lowest efficiency at 93.18% .

These values are calculated using the formula:

$$\eta = \frac{P_{PV}}{P_{load}} \times 100\%$$

Where P_{PV} and P_{load} are obtained from the PV Input Monitor and Output Power Monitor, respectively.

2.Analysis of the Curve

- The curve indicates that ANN outperforms other algorithms in terms of stability and accuracy under constant irradiance conditions.
- P&O and INC show stable performance but with slightly lower efficiencies compared to ANN .
- FLC exhibits larger fluctuations or slower response times, leading to reduced efficiency.

3.Factors Influencing Efficiency

- Response Speed : Algorithms like ANN and INC demonstrate faster and more precise responses to minor changes in environmental conditions.
- Fluctuations : P&O and FLC experience higher oscillations around the maximum power point (MPP), which reduces overall efficiency.
- Tracking Accuracy : ANN uses advanced predictive models to accurately locate the MPP, making it the most efficient.

4.Conclusion

- Best Algorithm : ANN achieves the highest efficiency (96.63%) due to its superior adaptability and precision.

- Alternative Choice : INC is a strong second choice (95.58%) for balancing efficiency and complexity.
- Limitations : P&O (94.72%) and FLC (93.18%) are less efficient and may only be suitable for simpler or low-cost applications.

5-Summary

Based on the provided data:

- Recommended Algorithm : ANN for achieving the highest efficiency and stability.
- Alternative Algorithm : INC if slightly lower efficiency is acceptable.
- Constraints : P&O and FLC are better suited for basic or cost-sensitive applications.

Variable irradiance (1000, 800, 600, 900 W/m²)

Table (IV.8): Table of efficiency in variable irradiance

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%

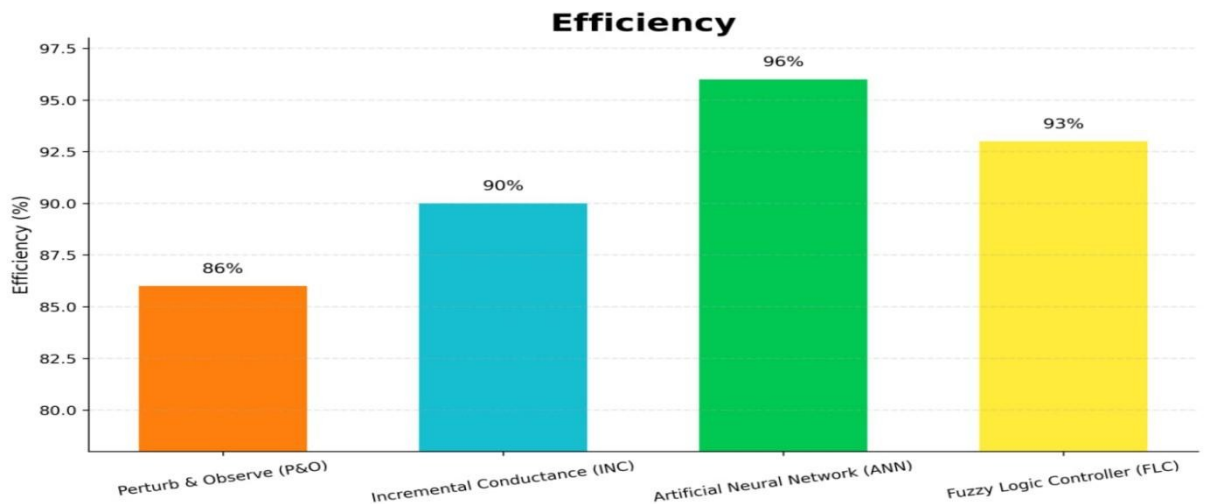


Figure (IV.38): Chart of efficiency in variable irradiance

The table (IV.9) and curve (IV.38) provide efficiency (η) values for four Maximum Power Point Tracking (MPPT) algorithms under variable irradiance (1000, 800, 600, 400 W/m²): Perturb and Observe (P&O), Incremental Conductance (INC), Artificial Neural Network (ANN) and Fuzzy Logic Controller (FLC).

1.Key observations**1. Highest Efficiency :**

- The Artificial Neural Network (ANN) algorithm achieves the highest efficiency at 95.06%, demonstrating its superior adaptability to rapidly changing irradiance levels.

2. Second Best :

- The Fuzzy Logic Controller (FLC) follows with an efficiency of 91.79%, showing reasonable performance but slightly lower stability compared to ANN.

3. Moderate Performance :

- The Incremental Conductance (INC) algorithm achieves 88.04%, indicating moderate adaptability to variable irradiance conditions.

4. Lowest Efficiency :

- The Perturb and Observe (P&O) algorithm has the lowest efficiency at 84.84%, reflecting its susceptibility to fluctuations and slower response under dynamic irradiance changes.

2.Analysis of the chart (Figure IV.33)

-The chart visually confirms the rankings observed in the table:

- ANN shows a consistently high efficiency curve, even as irradiance levels change.
- FLC follows closely but exhibits minor fluctuations during transitions between irradiance levels.
- INC demonstrates a stable but lower efficiency curve compared to ANN and FLC.
- P&O shows significant drops in efficiency during irradiance transitions, highlighting its limitations in dynamic environments.

3.Factors influencing efficiency**1.Adaptability to Rapid Changes :**

-Algorithms like ANN excel due to their ability to predict and adapt quickly to changes in irradiance.

-P&O struggles because it relies on perturbation, which is less effective under rapidly changing conditions

2.Stability :

-ANN and FLC maintain higher stability, minimizing oscillations around the maximum power point (MPP).

-P&O and INC exhibit more oscillations, reducing overall efficiency.

3.Complexity vs. Performance :

-ANN and FLC are computationally more complex but deliver superior performance in dynamic conditions.

-P&O and INC are simpler but less efficient under variable irradiance.

4.Conclusion

-Best Algorithm : ANN is the most effective under variable irradiance, achieving 95.06% efficiency due to its advanced predictive capabilities.

-Alternative Choice : FLC is a strong second choice (91.79%) for applications requiring good performance without the computational demands of ANN.

-Limitations : P&O (84.84%) and INC (88.04%) are less suitable for dynamic environments, as they struggle with rapid changes in irradiance.

5.Summary

Based on the provided data:

-Recommended Algorithm : ANN for optimal performance in variable irradiance conditions.

-Alternative Algorithm : FLC if computational complexity is a concern.

Constraints : P&O and INC are better suited for static or slowly changing environments.

Comparison of efficiency between constant an variable irradiances

The comparison of efficiency between the four algorithms (P&O, INC, ANN, and FLC) under both constant and variable irradiance conditions:

Constant Irradiance (1000 W/m²):

1. Artificial Neural Network (ANN) : 96.63%

2. Incremental Conductance (INC) : 95.58%
3. Perturb and Observe (P&O) : 94.72%
4. Fuzzy Logic Controller (FLC) : 93.18%

Variable Irradiance (1000, 800, 600, 900 W/m²):

1. Artificial Neural Network (ANN) : 95.06%
2. Incremental Conductance (INC) : 88.04%
3. Fuzzy Logic Controller (FLC) : 91.79%
4. Perturb and Observe (P&O) : 84.84%

Comparison and Analysis:

1. Artificial Network Neural (ANN) :

- Constant Irradiance : Highest efficiency at 96.63%.
- Variable Irradiance : Still the highest efficiency at 95.06%.
- Reason : ANN can adapt to changing conditions and learn from data, making it robust under both constant and variable conditions.

2. Incremental Conductance (INC) :

- Constant Irradiance : Second highest at 95.58%.
- Variable Irradiance : Efficiency drops significantly to 88.04%.
- Reason : INC is more sensitive to rapid changes in irradiance, which affects its performance under variable conditions.

3. Fuzzy Logic Controller (FLC) :

- Constant Irradiance : Lowest efficiency at 93.18%.
- Variable Irradiance : Efficiency increases slightly relatively to P&O but remains lower than ANN and INC.

Reason : FLC's rule-based system might handle variability better than P&O but still not as effectively as ANN

4. Perturb and Observe (P&O) :

- Constant Irradiance : Third highest at 94.72%.
- Variable Irradiance : Significant drop to 84.84%, the lowest among all.
- Reason : P&O struggles with fluctuating conditions because it continuously perturbs and observes, leading to oscillations and reduced efficiency when irradiance varies.

Cause of Differences Between Tables and Charts:

1. Constant vs. Variable Irradiance :

- The efficiency values are generally higher under constant irradiance compared to variable irradiance.
- This is expected because constant conditions provide a stable environment where algorithms can operate optimally.
- Under variable irradiance, the environmental changes challenge the adaptive capabilities of each algorithm, causing efficiency to drop.

2. Algorithm Sensitivity :

- Algorithms like P&O and INC show significant drops in efficiency under variable conditions due to their reliance on steady-state assumptions.
- ANN shows minimal decrease in efficiency due to its ability to learn and adapt to varying inputs.
- FLC lies in between, showing moderate adaptability but not as pronounced as ANN.

In conclusion, the Artificial Neural Network (ANN) demonstrates superior performance across both constant and variable irradiance conditions, while Perturb and Observe (P&O) exhibits the most significant decline in efficiency under variable irradiance. The differences in efficiency values between constant and variable conditions highlight the strengths and weaknesses of each algorithm's adaptability to environmental changes.

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.

General Conclusion

General Conclusion

This study began by laying the foundation for understanding solar radiation and photovoltaic energy conversion principles. It explained how solar cells harness the photovoltaic effect to generate electricity from sunlight, and discussed the modeling, characteristics, and factors influencing the efficiency of photovoltaic generators. Different photovoltaic cell types based on silicon crystal structures were also presented.

Building upon this, the crucial role of DC-DC converters in power management systems was explored. These converters facilitate efficient voltage conversion through various topologies like buck, boost, and buck-boost, enabling their widespread use across diverse industries.

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

This naturally led to an in-depth examination of MPPT principles, classifications, and implementation methods. Among the various MPPT algorithms evaluated, the Artificial Neural Network (ANN) approach emerged as the most effective and reliable. Its superior efficiency, stability, and adaptability under both steady and dynamic irradiance conditions make it the recommended method for maximizing energy extraction and ensuring robust performance in photovoltaic systems.

While other algorithms like Incremental Conductance showed better performance than the commonly used Perturb and Observe method, they still fell short of the advanced capabilities offered by ANN-based MPPT. Consequently, for optimizing photovoltaic system output and ensuring long-term, reliable operation, the ANN algorithm stands out as the optimal solution among the methods studied.

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