



People`s Democratic Republic of Algeria  
Ministry of Higher Education and Scientific Research  
University of Echahid Hamma Lakhdar - El Oued



Faculty of Technology  
Department of Electrical Engineering  
Dissertation

ACADEMIC MASTER  
Domain: Science and Technology  
Division: Electrical Engineering  
Specialty: Electrical Machines

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**Entitled:**

**FLC and ANN Based MPPT  
Controller for Solar PV System**

Dissertation Submitted in Partial Fulfillment of the Requirements for the Master  
Degree in Electrical Machines  
Publicly defended in: 03/06 /2024

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**Academic Year: 2023/2024**





# Acknowledgments

First and foremost, I would like to thank God “Allah” the Most Gracious and the Most Merciful, for blessing me with knowledge and giving me strength, courage, patience, and serenity during all these years of study.

I would also like to express my sincere appreciation to all those who contributed to the successful completion of this work. All thanks and appreciation to my honorable supervisor: Dr. KECHIDA Ridha for his unwavering support, guidance, and encouragement have been invaluable during the course of my project. His extensive expertise and diligent efforts have significantly enriched my academic journey.

Last but not the least, I am profoundly thankful to my parents. Their prayers, guidance, and unwavering support have been instrumental in my education. Their inspiration and encouragement have been a beacon of light, guiding me through the challenges and triumphs of my academic pursuit.



# الإهداء

بسم الله الرحمن الرحيم

(قل اعملوا فسيرى الله عملكم ورسوله والمؤمنين)

صدق الله العظيم

إله لا يطيب الليل إلا بشكره ولا يطيب النهار إلا بطاعته ... ولا تطيب اللحظات إلا

بذكره.. الله جل جلاله

إلى من بلغ الرسالة وأدى الأمانة ونصح الأمة ... نبي الرحمة ونور للعالمين

سيدنا محمد صلى الله عليه وسلم "

انتهت الرحلة.. لم تكن سهلة وليس من المفترض أن تكون كذلك.. ومهما طالت فستمضي بحلوها ومرها  
وها أنا الآن وبعون الله تعالى أتمم هذا العمل المتواضع.

وفي اللحظة الأكثر فخرا مُتدي عملنا هذا إلى من نحمل اسمه بكل افتخار (خيشة إبراهيم) ... الذي حصد  
الأشواك عن دربنا ليمهد لنا طريق العلم.. طاب لك العمر يا سيد الرجال وطبت لنا عمرا يا أبانا الغالي ...  
ترجو من الله أن يمد عمرك لترى ثمارا قد حان نضاجها بعد طول انتظار، وستبقى كلماتك نجوم مُتدي بها اليوم  
وغدا وإلى الأبد ...

إلى قلوبتنا الأولى ومعنى الحب والتفاني ... إلى بسمة الحياة وسر الوجود إلى من كان دعاؤها سر نجاحنا  
وحانها يلسم جراحنا.. إلى من ارشدتنا ورافقتنا في كل مشاوير حياتنا ولا تزال تفعل إلى الان.. اللهم احفظها  
ارزقها العفو والعافية.. أمانا الحبيبة.

إلى ضلعنا الثابت الذي لا يميل ... إلى من رزقناهم سندا وملاذنا الأول والأخير ....

إحوتنا: ياسين، رضا

وأحواتنا

إلى صديقات المواقف والسنين شريكات الدرب والظموح البعيد.. إلى من كانوا دوما موضع اتكاء عثرات

حياتنا نخص بالذكر: حسناء..

إلى كل الأهل والعائلة الكريمة كل باسمه ومقامه ...

**ملخص:** يُعتبر تتبُّع نقطة القدرة الأعظمية (MPPT) عنصراً أساسياً في تصميم أنظمة الخلايا الشمسية، فهو يُتيح تحسينَ خرج القدرة وتعزيزَ استقرارية النظام وموثوقيته . يقارن هذا البحثُ أداءَ تقنيات MPPT الشائعة : الإضطراب والمراقبة (P&O) ، موصلية التزايد (INC) ، والمنطق الضبابي (FLC) ، والشبكات العصبية الاصطناعية (ANN). من خلال تقييم هذه التقنيات في ظروف تشغيل مُتغيرة ضمن نظام خلايا شمسية غير مُتصلة بالشبكة، نهدف إلى تحديد النهج الأكثر فعالية لاستخراج القدرة على النحو الأمثل. تساهم هذه الدراسة في تحسين كفاءة وموثوقية أنظمة الخلايا الشمسية غير المُتصلة بالشبكة، وتعزيز حلول الطاقة المستدامة.

**كلمات مفتاحية:** الألواح الكهروضوئية، تتبع نقطة الاستطاعة العظمى (MPPT)، الاضطراب والمراقبة (P&O)، موصلية التزايد (INC)، المنطق الضبابي (FLC)، الشبكة العصبية الاصطناعية (ANN).

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**Abstract:** Effective Maximum Power Point Tracking (MPPT) is critical for photovoltaic (PV) systems, maximizing power output and enhancing system stability. This research compares the performance of common MPPT techniques: Perturb and Observe (P&O), Incremental Conductance (INC), Fuzzy Logic Control (FLC), and Artificial Neural Network (ANN). By evaluating these techniques under varying operating conditions in an off-grid PV system, we aim to identify the most effective approach for optimal power extraction. This research contributes to improved efficiency and reliability of PV systems, promoting sustainable energy solutions.

**Keywords:** Photovoltaic system, PV, MPPT, P&O, INC, Fuzzy Logic. ANN.

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**Résumé :** Le suivi du point de puissance maximale (MPPT) est un élément crucial dans la conception des systèmes photovoltaïques (PV) hors réseau. Il permet d'optimiser la puissance de sortie et d'améliorer la stabilité et la fiabilité du système. Cette recherche compare les performances de techniques courantes de MPPT : Perturb and Observe (P&O), Incrémental Conductance (INC), Fuzzy Logic Control (FLC) et Réseau de neurones artificiels (ANN). En évaluant ces techniques dans des conditions de fonctionnement variables au sein d'un système PV hors réseau, nous visons à identifier l'approche la plus efficace pour une extraction de puissance optimale. Cette recherche contribue à l'amélioration de l'efficacité et de la fiabilité des systèmes PV hors réseau, favorisant ainsi les solutions d'énergie durable.

**Mots clés :** Photovoltaïque système (PV), MPPT, P&O, INC, FLC. ANN.

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## List of abbreviations

<b><i>Cdc</i></b>	dc link capacitor
<b><i>Ci</i></b>	Input capacitor
<b><i>Co</i></b>	Output capacitor
<b><i>fsw</i></b>	Switching frequency
<b><i>Icc</i></b>	Short circuit current
<b><i>icrr</i></b>	Short-circuit current under STC conditions
<b><i>id</i></b>	Current across the diode
<b><i>I<sub>max</sub></i></b>	Maximum current
<b><i>iph</i></b>	Photo-current
<b><i>ipv</i></b>	PV current
<b><i>Is</i></b>	Saturation current
<b><i>Ki</i></b>	Temperature coefficient of the short-circuit current
<b><i>Lf</i></b>	Output inductance filter
<b><i>np</i></b>	Cells connected in parallel
<b><i>Ns</i></b>	Number of cells connected in series
<b><i>ns</i></b>	Cells connected in series
<b><i>P<sub>max</sub></i></b>	Maximum power
<b><i>Rf</i></b>	output inductance filter resistance
<b><i>rp</i></b>	Parallel resistor
<b><i>rs</i></b>	Series resistor
<b><i>Vdc</i></b>	dc link voltage
<b><i>vd</i></b>	Diode voltage
<b><i>Vg</i></b>	Grid voltage
<b><i>V<sub>max</sub></i></b>	Maximum voltage
<b><i>Voc</i></b>	Open circuit voltage
<b><i>vpv</i></b>	PV voltage
<b><i>Vrip</i></b>	voltage ripple
<b><math>\lambda</math></b>	Wavelength
<b>ac</b>	Alternative current
<b>AI</b>	Artificial Intelligence
<b>A</b>	Cell's area
<b>C</b>	Capacitor
<b>dc</b>	Direct current

<b>E</b>	Energy
<b>f</b>	Frequency
<b>GD</b>	Gradient Descent
<b>G</b>	Solar irradiance
<b>h</b>	Plank's constant
<b>IncCond</b>	Incremental Conductance
<b>K</b>	Boltzmann's constant
<b>L</b>	Inductance
<b>MPPT</b>	Maximum Power Point Tracking
<b>MSE</b>	Mean Squared Error
<b>NN</b>	Neural Network
<b>n</b>	Ideality factor of the diode
<b>OCV</b>	Open Circuit Voltage
<b>P&amp;O</b>	Perturb and Observe
<b>PLL</b>	Phase Locked Loop
<b>PVG</b>	Photovoltaic Generator
<b>PV</b>	Photovoltaic
<b>q</b>	Electron charge
<b>SGD</b>	Stochastic Gradient Descent
<b>THD</b>	Total Harmonic Distortion
<b>T</b>	Temperature
<b>W</b>	Weight
<b>w</b>	Pulsation

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# **General Introduction**

# GENERAL INTRODUCTION

Global energy consumption is increasing due to population growth and industrialization. Currently, the majority of electrical energy production relies on non-renewable resources such as coal, natural gas, and oil, which have harmful environmental effects. As a result, there is an urgent need to develop clean and renewable energy sources like solar, wind, and bioenergy. These renewable energy sources are environmentally friendly and contribute to the reduction of CO<sub>2</sub> emissions. Additionally, they can be produced on a small scale or locally, improving their accessibility and sustainability.

The solar energy possesses a wide range of applications and demonstrates significant flexibility, which enhances its overall utility. To ensure optimal energy transfer, various equipment is connected to the photovoltaic generator. The power output of a photovoltaic system is influenced by factors such as temperature, irradiance, and load. Therefore, implementing a Maximum Power Point Tracking (MPPT) algorithm is essential to ensure that the photovoltaic generator operates at maximum efficiency.

The nonlinear behavior of photovoltaic systems (PV) poses challenges for power control. Moreover, the energy conversion efficiency is contingent upon various factors, including the type of PV cells utilized, the converters technologies, the MPPT algorithm, and the surrounding environmental conditions. The choice of MPPT algorithm significantly impacts the efficiency of the solar system. The traditional algorithms exhibit numerous drawbacks, particularly their inability to accurately track maximum power under rapidly changing meteorological conditions.

So, the motivation is to develop an algorithm capable of improving efficiency by leveraging the strengths of multiple techniques, including tracking speed, precision, stability, and adaptability to sudden environmental changes. Artificial intelligence (AI) presents an opportunity to address this challenge by employing an MPPT technique based on Neural Networks (NN).

The objective of this work is to implement various MPPT techniques and apply them at the adaptation stage, followed by simulations to compare the obtained results. Our thesis is divided into four chapters.

In the first chapter, we will present photovoltaic energy. We will explain the operating principle, the main characteristics, and the parameters of a solar cell. Finally, we will discuss the advantages and disadvantages of photovoltaic energy.

The second chapter is dedicated to presenting the various types of maximum power point tracking (MPPT) methods found in the literature. In our case study, the theoretical aspect will be developed for two control strategies: "P&O" and "INC."

In the third chapter, we will present Fuzzy Logic Control (FLC) technique for PV-MPPT systems will be presented, along with an explanation of fuzzy logic control. Additionally, we will discuss the advantages and disadvantages of FLC-MPPT.

The fourth chapter in this thesis the ANN-based algorithms are simulated, and tested in different conditions. Some characteristics of the algorithm are studied: efficiency, time for the estimation of the Maximum Power Point, reaction to change of the PV system. These performance parameters are compared with the same ones of different algorithms, in order to have a useful comparison between different technologies that can guide in the choice of the proper algorithm.

Finally, we will conclude our thesis with a general conclusion chapter that will summarize the significance of our study and highlight the main findings and recommendations.

**Chapter I.**  
**Solar Photovoltaic**  
**System**

# Chapter I. Solar Photovoltaic System

## I.1.Introduction

Since the mid-1990s, renewable energies have been experiencing increasing popularity that seems to strengthen year after year. These energies, mainly drawn from the five elements: earth, water, air, fire, and the sun, are among the oldest used by humanity. They are inexhaustible and have been used since time immemorial. The term "renewable energies" now encompasses various sectors whose implementation does not in any way deplete the initial resource. These renewable energy sources are mainly used to produce electricity. Photovoltaic cells play an essential role in transforming solar energy into electricity without requiring mechanical means or chemical processes. This technology is constantly evolving, as are other components of photovoltaic systems. However, it is already a preferred option for ensuring electricity supply in many situations.

## I.2. Overview of Renewable Energies

Renewable energies are derived from unlimited resources and span various technological sectors, depending on the source of the exploited energy and the resulting useful energy. Several types of renewable energy sources exist, including hydroelectric energy, wind energy, biomass energy, and photovoltaic energy. These renewable energy sources originate directly or indirectly from the sun, ensuring their continuous availability as long as the sun shines.

Photovoltaic energy is the most recent addition to the array of renewable energies, providing notable advantages such as being non-polluting, flexible, and reliable. Photovoltaic systems have been in use for 40 years, initially introduced through space programs for radio transmission in satellites. Subsequently, their applications expanded to include sea beacons and the powering of isolated sites worldwide, utilizing batteries to store electrical energy during periods without sunlight, [01]. There are various types of renewable energies:

### I.2.1. Hydraulic Energy

Hydraulic energy is a highly low-emission renewable energy source. This renewable energy exploits the movements of water driven by the sun and gravity through the water cycle, tides, and marine currents. (See Figure I.1).

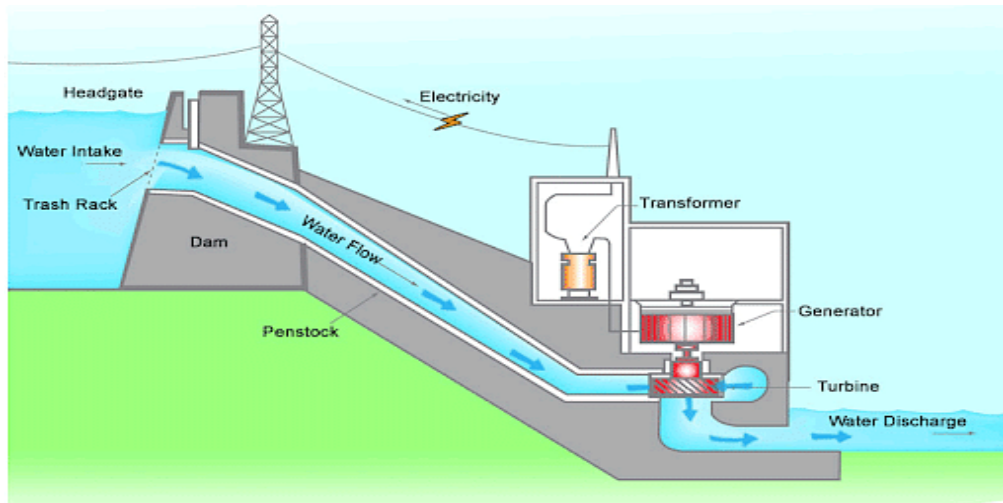


Figure (I.1). Hydraulic Power Plant.[02]

### I.2.2. Geothermal Energy

Geothermal, derived from the Greek words "geo" (earth) and "thermos" (heat), encompasses both the scientific study of internal thermal phenomena within the Earth and the technology aimed at harnessing it. In broader terms, geothermal also refers to the geothermal energy arising from the heat of the Earth, which is converted into usable heat. (See Figure I.2)

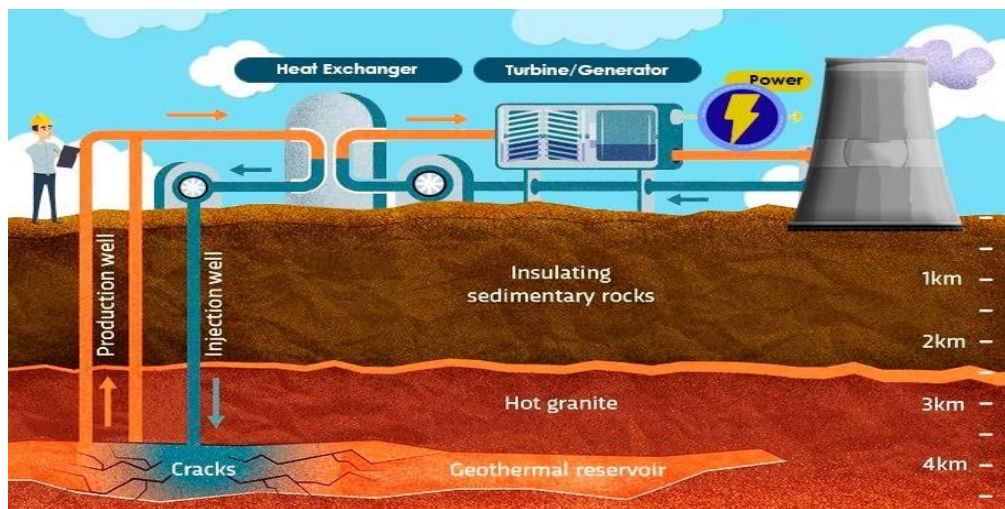


Figure (I.2). Geothermal Energy. [03]

### I.2.3. Biomass Energy

In the field of energy, specifically bioenergy, the term biomass refers to all organic matter of plant, animal, or fungal origin that can serve as a source of energy. This can be achieved through combustion (e.g., wood energy), methanization (biogas), or further chemical transformations (agrofuel). The energy derived from biomass is considered renewable and sustainable as long as there is no overexploitation of the resource. [01]

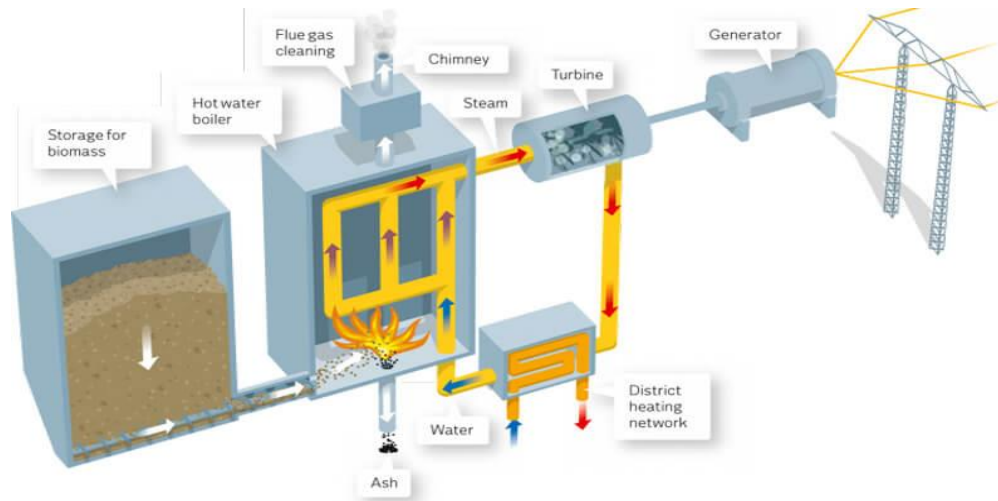


Figure (I.3). Biomass Power Plant. [04]

#### I.2.4. Marine Energy

Marine energy is a renewable energy source that leverages the natural resources of the seas and oceans to generate electricity, primarily by harnessing the movements of these waters. Given that water covers a significant portion of our planet, predominantly through seas and oceans, it represents a substantial yet currently underutilized energy source. Marine energy produces no greenhouse gas emissions, and its raw materials are abundantly available in numerous countries worldwide.

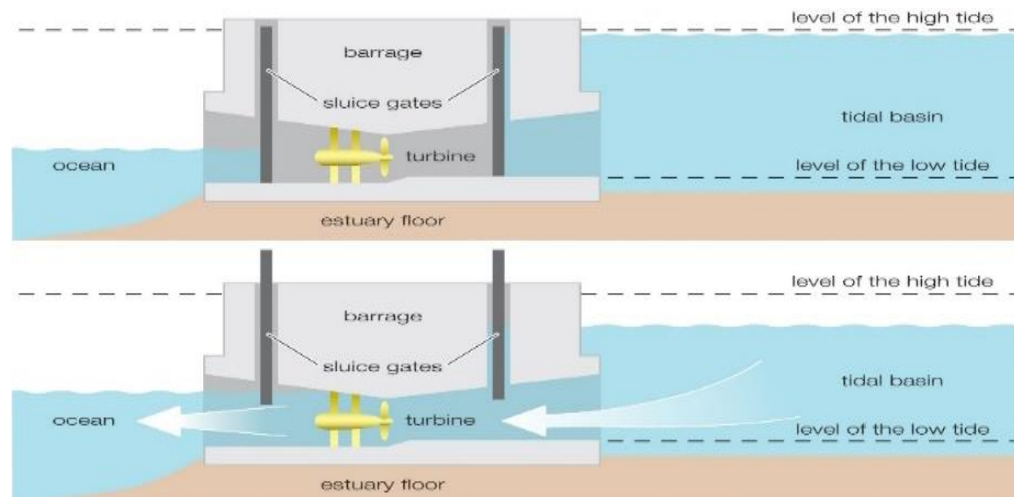


Figure (I.4). Tidal Power Plant. [05]

#### I.2.5. Wind Energy

Wind energy is a power source that relies on the wind. The uneven heating of the Earth by the sun creates zones of different temperatures and atmospheric pressure worldwide. These pressure differences give rise to air movements, known as wind. This energy is harnessed to generate electricity in wind turbines, also known as wind generators, utilizing the force of the wind. (See Figure I.5) [01]

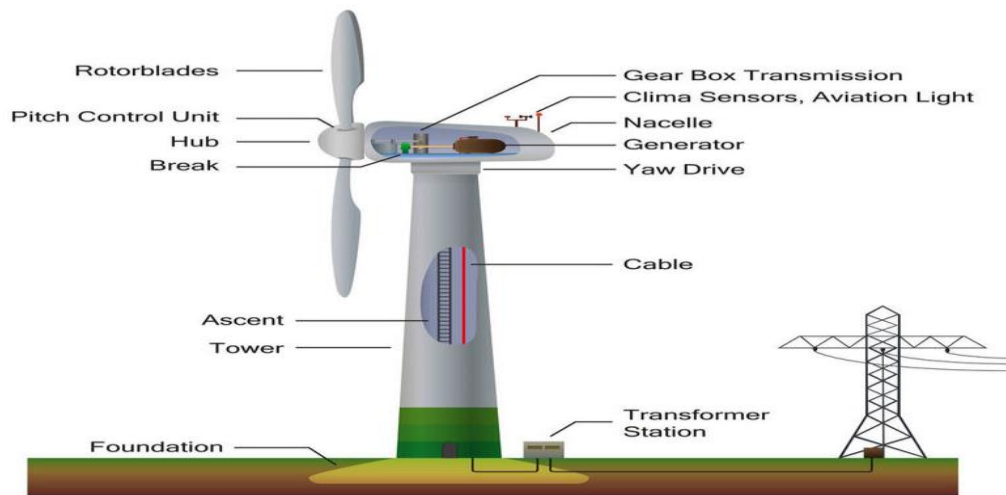


Figure (I.5). Wind Turbine. [06]

### I.2.6. Solar Energy

Solar radiation is the most uniformly distributed and abundant energy resource on Earth. The energy emitted by the sun and absorbed by the Earth in a single hour could potentially fulfill the world's energy requirements for an entire year. The sun continuously emits an enormous amount of radiant energy into the solar system, and the Earth captures only a small fraction of this solar output, (Figure I.6).

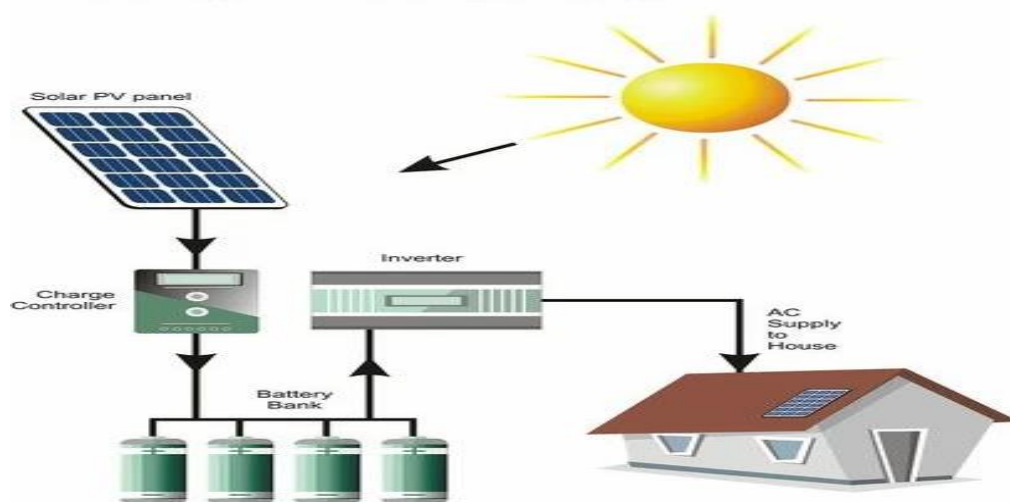


Figure (I.6). A Solar Installation. [07]

### I.3. Historical Background

The development of photovoltaic systems is the result of continuous work over many years and contributions from various scientists throughout history.

**1839:** French physicist *Antoine Becquerel* discovered the photovoltaic effect.

**1875:** *Werner Von Siemens* presented a paper on the photovoltaic effect in semiconductors before the Berlin Academy of Sciences.

**1887:** The photoelectric effect was understood and presented in 1887 by *Heinrich Rudolf Hertz*, who published his results in the scientific journal *Annalen der Physik*.

**1905:** *Einstein* explained the photoelectric phenomenon in 1905 and received the *Nobel Prize* in Physics for his work in 1921.

**1954:** American researchers, *Chapin*, *Pearson*, and *Prince* at Bell Labs developed the first silicon photovoltaic cell with an efficiency of 4 %.

**1958:** A photovoltaic cell with 9% efficiency was developed. The first Vanguard satellites powered by photovoltaic cells were sent into space.

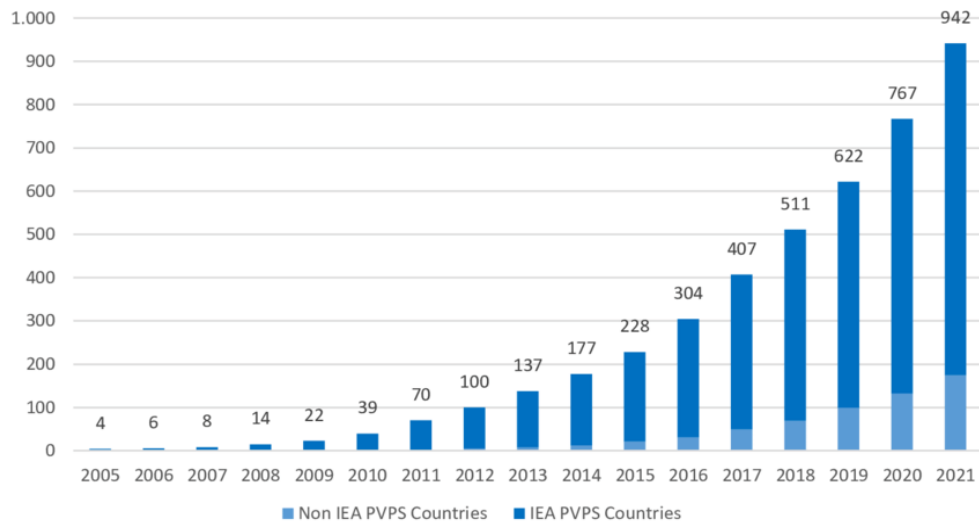
**1973:** The first house powered by photovoltaic cells was built at the University of Wilmington in Delaware, USA.

**1983:** The first solar-powered car traveled a distance of 4,000 km in Australia.

**1995:** Grid-connected photovoltaic roof programs were launched in Japan and Germany, becoming more widespread since 2001.

**2005:** the first photovoltaic solar power plant of the Prime Energy Group was connected to the grid in Weil am Rhein, Baden-Württemberg, Hagenheimer Strasse 17.

The following figure (I.7) shows the evolution of the capacity and annual additions of global photovoltaic solar energy from 2011 to 2021 [11].



**Figure (I.7).** Evolution of Installed Capacity of Photovoltaic Solar Energy Worldwide

## I.4. Types of Photovoltaic Cells

There are different types of solar panels, the most commonly used are:

### I.4.1 Monocrystalline silicon cells:

- Very good efficiency: 14 to 20%.
- Life Span: significant (30 years).
- Manufacturing cost: high.
- Power: 100 to 150 W<sub>c</sub>/m<sup>2</sup>.
- Low efficiency under low illumination.
- Efficiency loss with temperature increase.
- Manufacturing: elaborated from a melted silicon block that solidified forming a single crystal.



Figure (I.8). Monocrystalline silicon cell

### I.4.2. Polycrystalline silicon cell:

- Good efficiency: 11 to 15%.
- Lifespan: significant (30 years).
- Manufacturing cost: cheaper than monocrystalline panels.
- Power: 100 W<sub>c</sub>/m<sup>2</sup>.
- Low efficiency under low illumination.
- Efficiency loss with temperature increase.
- Manufacturing: elaborated from electronic-grade silicon which, upon cooling, forms multiple crystals.

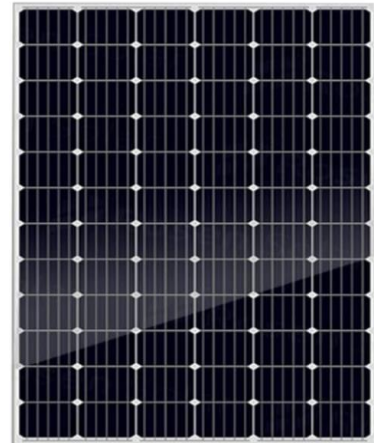


Figure (I.9). Cellule au silicium poly cristallin

### I.4.3. Amorphous silicon cell:

- Low efficiency: 5 to 9%.
- Lifespan: fairly significant (20 years).
- Manufacturing cost: inexpensive.
- Power: 50 W<sub>c</sub>/m<sup>2</sup>.
- Operates adequately under low illumination.
- Less sensitive to high temperatures.
- Low efficiency in full sunlight.
- Performance decreases over time.

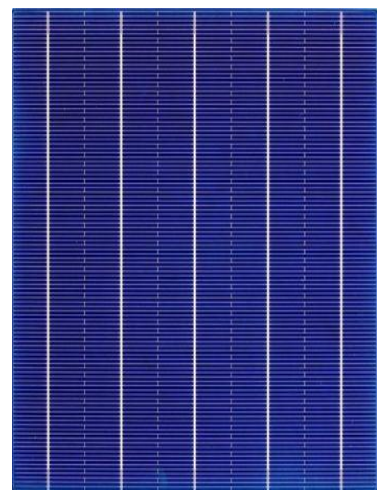


Figure (I.10). Amorphous silicon cell

## I.5. Association of Photovoltaic Modules

Modules can be connected in series and parallel to increase voltage and current intensity for practical applications. However, it is important to take precautions, as the presence of less efficient cells or the shading of one or more cells (due to shadows, dust, etc.) can permanently damage the cells.

### I.5.1 Series Connection

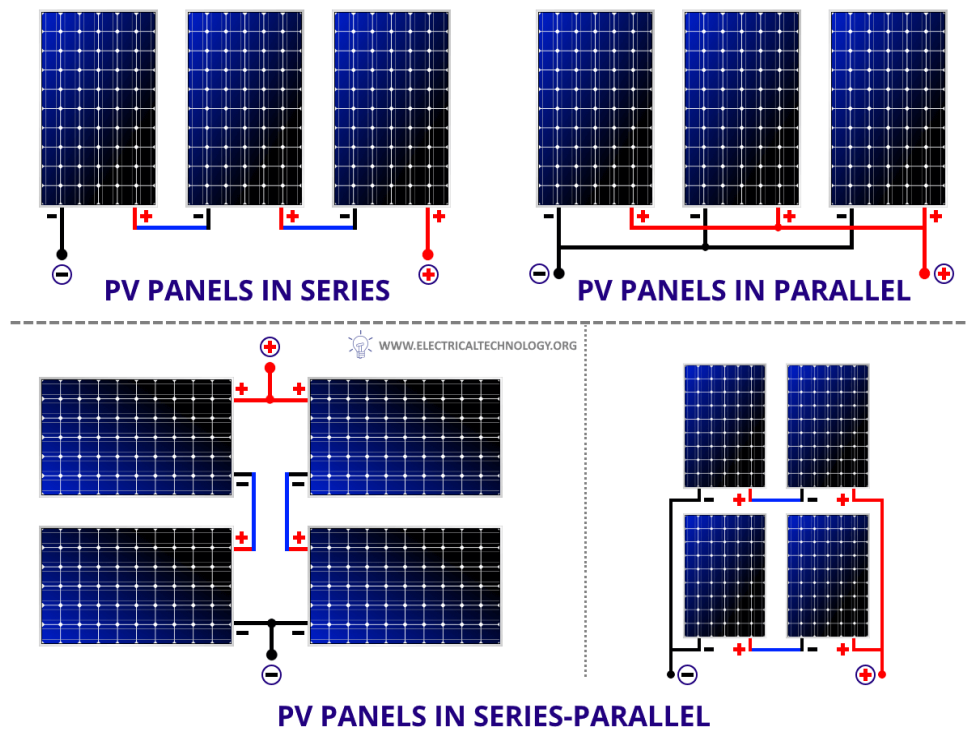
The individual cell, the basic unit of a photovoltaic system, produces only a very low electrical power, typically around 0.5 W with a voltage of less than one volt. To generate more power, cells are assembled to form a module (or panel). The series connection of cells provides a voltage equal to the sum of individual voltages and a current equal to that of a single cell.

### I.5.2 Parallel Connection

By connecting identical modules in parallel, the voltage across the branch is equal to the voltage of each module, and the current increases proportionally to the number of modules in parallel in the branch.

### I.5.3 Series-Parallel Connection

To achieve satisfaction in both current and voltage, it is necessary to use a mixed arrangement, namely Series-Parallel [13].



**Figure (I.11).** Series, Parallel & Series-Parallel Connection of Solar Panels.

## I.6. Different Photovoltaic Systems

### I.6.1. Stand-alone systems

These kinds of systems are made up of an inverter (for DC to AC conversion), a PV panel, and a battery bank for storage. Stand-alone systems, as pictured in figure (I-12), are most suitable for areas featuring limited energy requirements and readily available solar insolation [14].

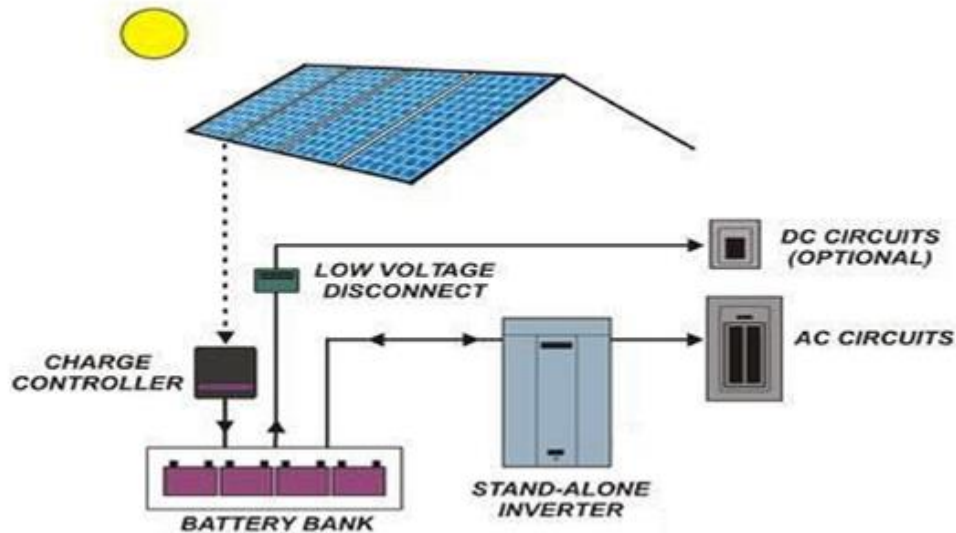


Figure (I.12). Stand-alone PV system.

### I.6.2. Grid-connected systems

As shown in Figure (I-13), grid-connected systems feature PV solar modules that supply electrical power through a high-quality inverter and, unlike stand-alone systems, are directly connected to power lines. The inverter in grid-connected systems changes PV-generated DC to AC. It is worth noting that generating stations based on PV modules are also considered grid-connected systems, as they produce a large amount of power, which they then add to the grid power.

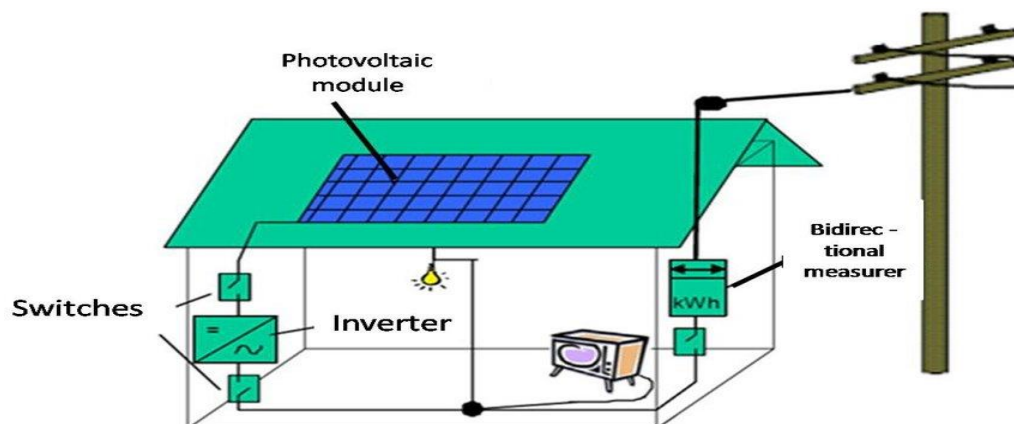


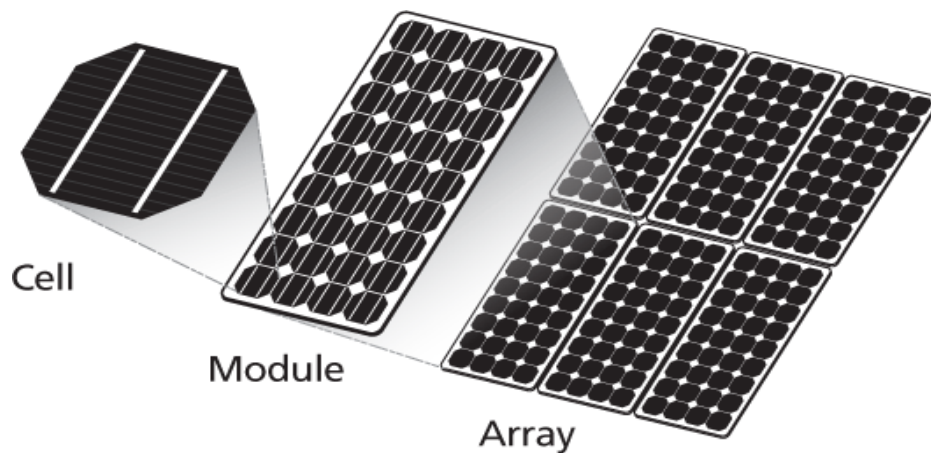
Figure (I.13). Grid-connected PV system.

## I.7. Photovoltaic generator PVG

The photovoltaic cell is a low-power electrical generator, it's not sufficient for most domestic and industrial applications. In order to provide the necessary power for load a number of PV cells must be connected together in series and/or parallel to form a module.

### I.7.1 Design and features of the PVG

The modules can be connected to each other in series and/or parallel to form photovoltaic generators (PV array). The figure (I.14) shows the constitution of a photovoltaic array [11].



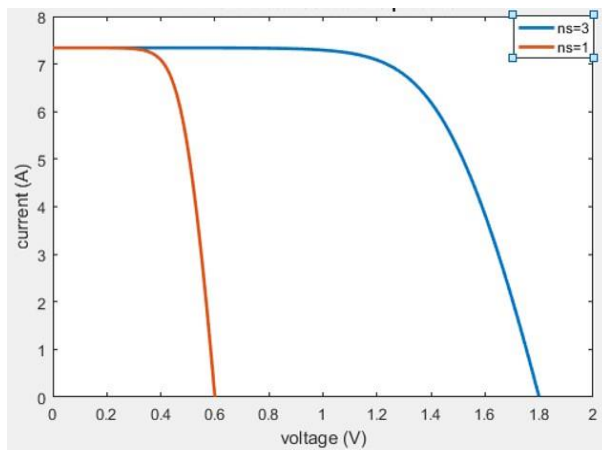
**Figure (I.14).** The constitution of a photovoltaic array.

An association of  $n_s$  cells in series increases the voltage, the cells will be crossed by the same current. The output voltage is the addition of every PV cell voltage as can be noticed from the next equation and figure (I.15).

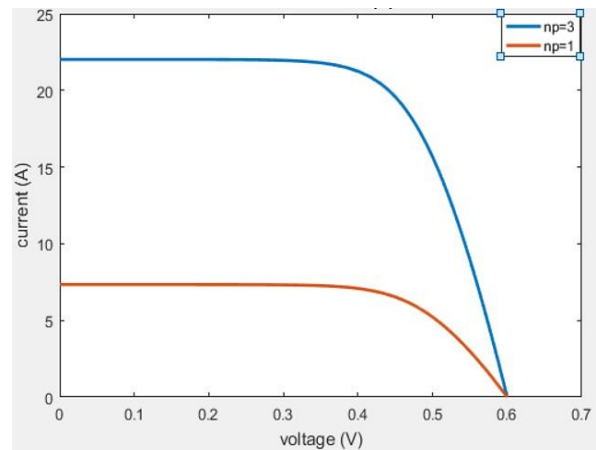
$$\begin{aligned} V_{OC_{n_s}} &= n_s \cdot V_{OC} \\ I_{SC_{n_s}} &= I_{SC} \end{aligned} \quad (I.1)$$

On the other side, a parallel association of  $n_p$  cells increases the current provided by the generator. A number of cells connected in parallel are under the same voltage. The output current is the addition of every PV cell current as presented in the equation (I.2) and the figure(I.16).

$$\begin{aligned} V_{OC_{n_p}} &= V_{OC} \\ I_{SC_{n_p}} &= n_p \cdot I_{SC} \end{aligned} \quad (I.2)$$



**Figure (I.15).** I-V characteristic for  $n_s$  PV cells.



**Figure (I.16).** I-V characteristic for  $n_p$  PV cells.

The operating voltage depends on the configuration of the power supply system, and the surface area of the module is variable depending on the constructor. The assembly of the modules in series and/or in parallel will make it possible to adjust different voltages and powers [11].

### I.7.2. Protection of the PVG

To assure the continuity of supply under different conditions and to avoid damage of the PV cells there are two types of protection available:

#### A. Series

The current flowing through the cells is the same and the voltages add up. Under nonuniform conditions of radiation for one cell of them, the cell may be submitted to the voltage of the other cells applied in reverse and it becomes like a receiver by dissipating a large amount of power and be destroyed if the break-down voltage of diode is exceeded. So, a diode must be connected in parallel (bypass-diode) to protect that cell. But, for Economic reasons adding a bypass diode to every cell isn't available. Therefore is placed two bypass-diode for a normal thirty-six cell module to avoid the hot-spot damage in order to ensure the protection of cells with less bypass diodes.

#### B. Parallel

The cells are submitted to the same voltage and the currents add up. Under nonuniform conditions of radiation for one cell of them, the cell may be submitted to reverse current produced by the other cells and dissipate power and be destroyed. To prevent reverse current, a diode must be connected in series (blocking-diode) [16]. The figure (I.17) indicates the bypass diode and blocking diode.

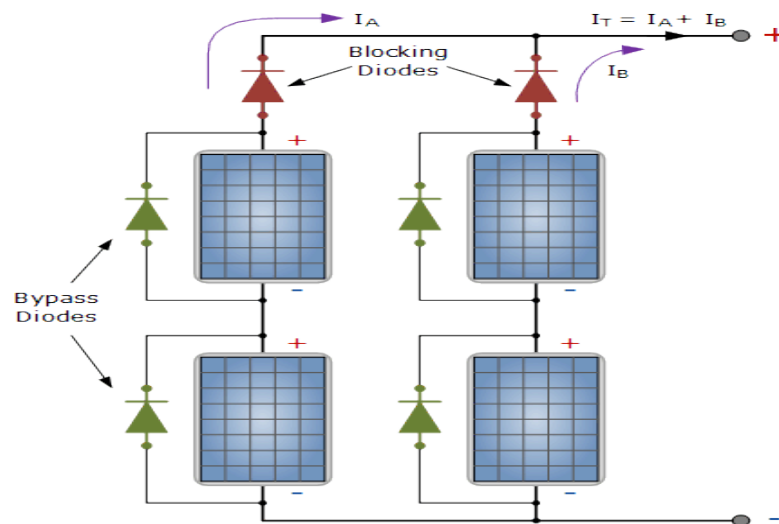


Figure (I.17). Bypass diode and blocking diode.

## I.8. The characteristics of a photovoltaic cell

The electrical properties of the cell are synthesized in a graph called the current-voltage characteristic, illustrated in figure (I.18).

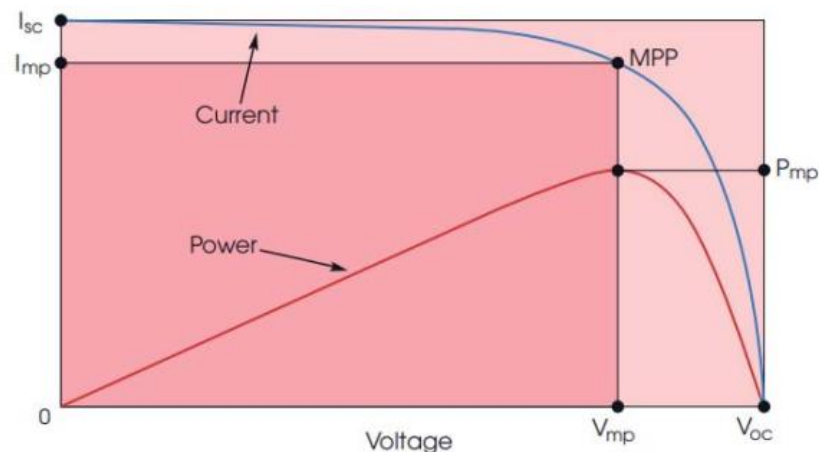


Figure (I.18). Current-voltage characteristic.

The three important points on this curve are as follows:

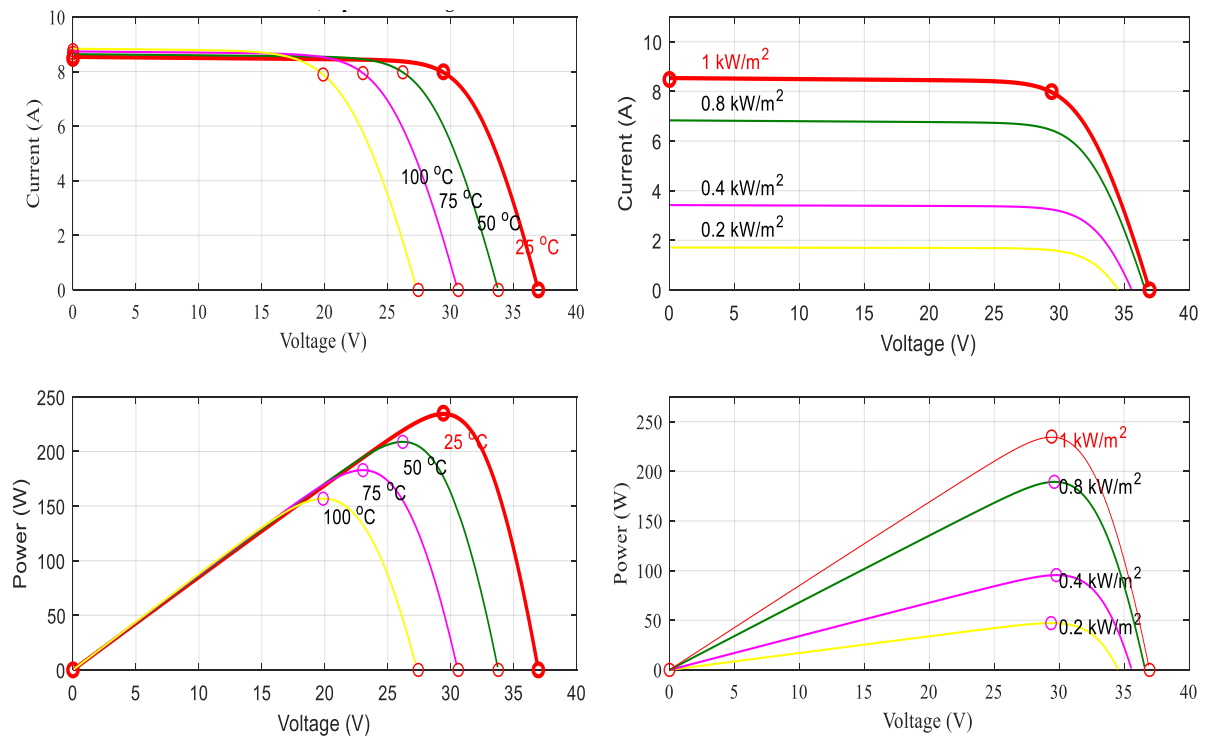
- **The maximum power point (MPP):** It is obtained for an optimal voltage and current, denoted  $V_{opt}$ ,  $I_{opt}$  (also referred to as  $V_{mp}$ ,  $I_{mp}$ ).
- **The short-circuit current ( $I_{sc}$ ):** This is the current flowing through the photovoltaic cell when it is short-circuited, meaning when the positive terminal is connected to the negative terminal and the voltage across its terminals is zero. In this case, the power supplied by the cell ( $P = V \times I$ ) is zero.
- **The open-circuit voltage ( $V_{oc}$ ):** This is the voltage across the terminals of the cell when it is in an open circuit, meaning when the positive and negative terminals are electrically isolated from any other electrical circuit and the current passing through it is zero. In this case, the power supplied by the cell ( $P = V \times I$ ) is zero [17].

Taking for example a cell from the SunPower SER-235P module, this module has the following characteristics at 1000 ( $\text{W}/\text{m}^2$ ) and  $25^\circ\text{C}$ :

**Table (I.1).** Characteristics of the SunPower SER-235P module.

<b>P (W)</b>	<b><math>V_{oc}</math>(V)</b>	<b><math>I_{cc}</math> (A)</b>	<b><math>V_{mp}</math> (V)</b>	<b><math>I_{mp}</math> (A)</b>
235	36.96	8.48	29.42	7.99

The following figures represent the characteristics of the PV panel in operation for different temperatures and solar irradianations.



**Figure (I.19).** Characteristics of a PV for different temperatures and irradianations conditions.

## I.9. Advantages and disadvantages of photovoltaic energy

### A. Advantages

- ✓ Free and Non-Polluting: Solar energy is free and does not cause pollution.
- ✓ Reliability and Longevity: Solar installations are reliable, and their lifespan is long.
- ✓ Fixed Structure: Solar installations have a fixed structure.
- ✓ Low Maintenance Cost: The cost of maintenance for solar installations is low.
- ✓ Flexibility: Solar systems can be sized according to needs, and they offer modularity.
- ✓ Unlimited Potential: Utilizing just 5% of desert surfaces could power the entire planet.

### B. Disadvantages

- ✗ High Installation Cost: The initial installation cost of solar systems can be high.
- ✗ Relatively Low Efficiency: The efficiency of photovoltaic effects is relatively low.

- ✗ **Reduced Power in Unfavorable Weather:** Power output is reduced during unfavorable weather conditions, such as cloudy days.
- ✗ **Necessity of Electrical Energy Storage:** For autonomous systems, storing electrical energy in chemical form (batteries) is necessary.
- ✗ **Environmental Impact:** Despite the pollution-free electricity produced, the manufacturing, installation, and disposal of solar panels have an environmental impact. [18]

## I.10. MPPT Techniques

The challenging aspect of this solar power is its dynamic nature, which can result invariable power and voltage levels based on the surrounding conditions. To operate PV unit at their highest possible power, a number of MPPT approaches are employed. Nowadays, the most demanding area of research on solar energy is solar power forecasting and tracking of maximum power point on P-V cell V-I characteristics. [19]

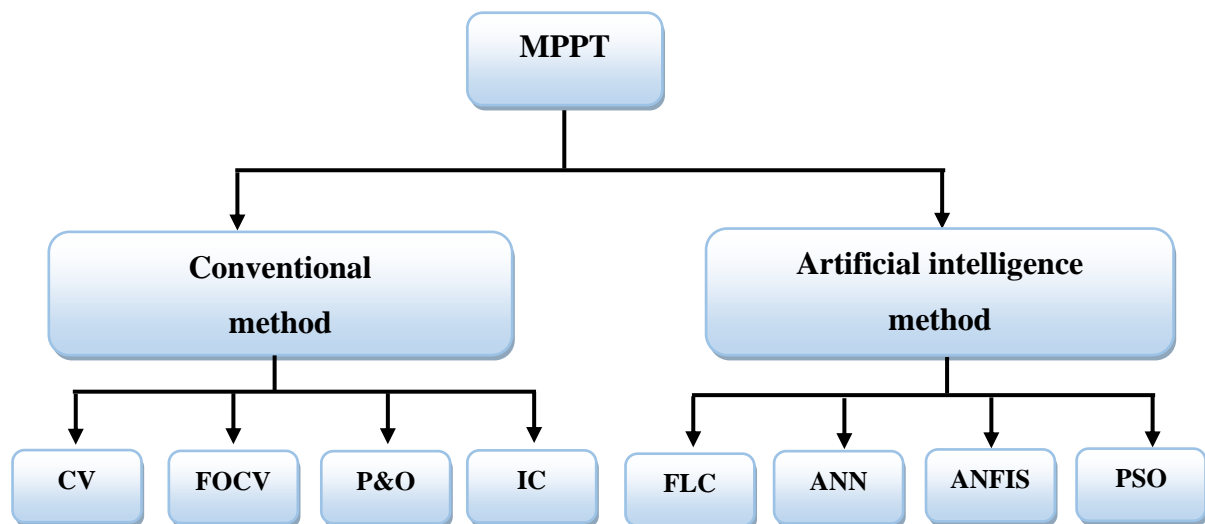


Figure (I.20). Common types of MPPT methods for PV systems. [20]

The three most common MPPT algorithms are:

### 1. Perturbation and observation (P&O)

This algorithm perturbs the operating voltage to ensure maximum power. While there are several advanced and more optimized variants of this algorithm.

### 2. Incremental conductance

This algorithm, compares the incremental conductance to the instantaneous conductance in a PV system. Depending on the result, it increases or decreases the voltage until the maximum power point (MPP) is reached. Unlike with the P&O algorithm, the voltage remains constant once MPP is reached [21].

### 3. Fuzzy Logic

The Fuzzy Logic (FL) is a rule-based algorithm with robustness to solve non-linear optimization problem. Fuzzy Logic method follows three steps like fuzzification, inference

fuzzy rules and defuzzification for its MPP tracking. In these steps, Fuzzy inference and designing of fuzzy rules decides the optimal performance of the system. But then, to design Fuzzy rules abundant knowledge and high amount of training is needed.

#### **4. Artificial Neural Network**

Artificial Neural Network is a technique derived from the behavior of neurons. Since it is an algorithm of artificial intelligence, ANN has the ability to think of its own. But then, much knowledge is needed to train the neurons present in the algorithm. From the survey, it is very obvious that ANN involves three layers in MPPT installation. Due to its enlarged optimization scope, the ANN is preferred to implement in combination with other conventional MPPT techniques to extract maximum power from a PV array [22].

### **I.11. Conclusion**

Solar energy systems can be simple or complex, depending on the needs of the solar user. The common component of all systems will be the solar module or solar array. Solar modules, though similar in design (silicon crystalline-type) will vary by size and power produced.

**Chapter II**  
**Modeling of PV system**  
**with different MPPT**  
**techniques**

# Chapter II. Modeling of PV system with different MPPT techniques

## II.1. Introduction

The Maximum Power Point Tracking (MPPT) algorithm is primarily used to extract the maximum possible power from PV modules, given the irradiance and temperature conditions at any particular moment. The role of the MPPT controller is to identify the maximum power point (MPP) of the solar photovoltaic system.

In this chapter, the most popular MPPT control algorithms are presented. First, the different types of static converters that can be used in PV systems are examined. Then, MPPT control algorithms such as Perturb and Observe (P&O) and Incremental Conductance (INC) are tested. Mathematical modeling of the PV system was implemented and tested in MATLAB/SIMULINK based on the fundamental equations of an equivalent circuit of PV cells. Finally, the desired PV system was simulated along with a Maximum Power Point Tracking (MPPT) system.

## II.2. Model of a Cell

A PV cell can be modeled based on the equation defining the static behavior of the PN junction of a classical diode. Thus, figure (II.1) illustrates the equivalent electrical circuit of a real PV cell [13].

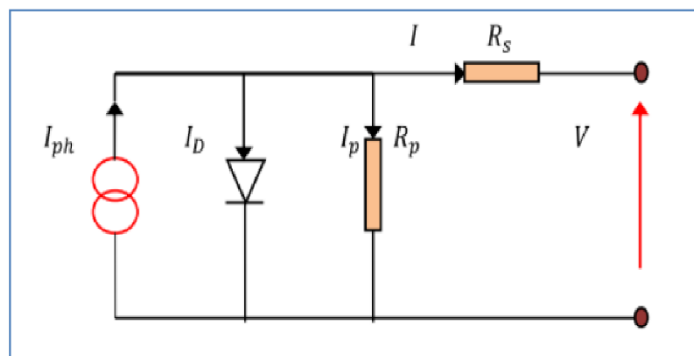


Figure (II.1). Equivalent Diagram of the PV Cell.

$$I = I_{ph} - I_0 \left( e^{\frac{v + IR_s}{nV_r}} - 1 \right) - \frac{V + IR_s}{R_p} \quad (II.1)$$

Where the diode current is given by the equation:

$$I_D = I_0 \left( e^{\frac{v + IR_s}{nV_T}} - 1 \right) \quad (II.2)$$

The reverse saturation current of a diode is given by:

$$I_0 = I_{sc} / \left( e^{\frac{V_{oc}}{nV_T}} - 1 \right) \quad (II.3)$$

If we assume that the parallel resistance is infinite ( $R_s = \infty$ ), equation (II.1) becomes:

With:

$$I = I_{sc} - I_0 \left( e^{\frac{V + R_s I}{nV_T}} - 1 \right) \quad (II.4)$$

I: The current supplied by the cell.

V: The voltage across the cell.

$$I = I_{sc} - I_0 \left( e^{\frac{V + R_s I}{nV_T}} - 1 \right) \quad (II.5)$$

### II.3. Power Stages

To ensure the suitable PV array-load a power stage is needed. In the next section a study of DC/DC converters is performed.

#### II.3.1. DC/DC Converter

There are many types of DC/DC converters can be connected with the PV generator according to the load voltage (Buck, Boost and Buck Boost). The connection via a power stage [23] shown in the figure (II.2):

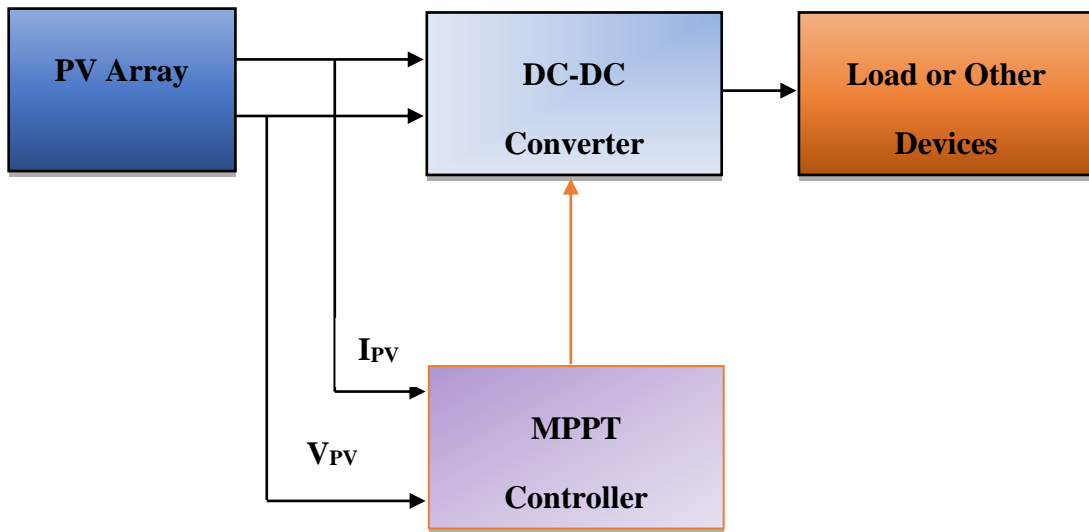


Figure (II.2). PVG-load connection via power stage.

### II.3.2. Boost Converter

The boost converter is a power converter with a dc output voltage higher than its dc input voltage. It contains two semiconductors (diode, switch) and at least one energy storage element. The output capacitor is added to reduce output voltage ripple. Also, the boost converter is called a step-up converter. The figure (II.3) indicates the circuit of the boost converter [23].

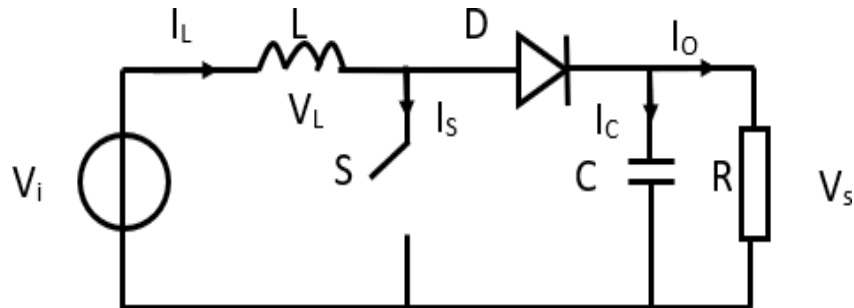


Figure (II.3). The Circuit of the Boost Converter.

The figure (II.4) shows the switch's state:

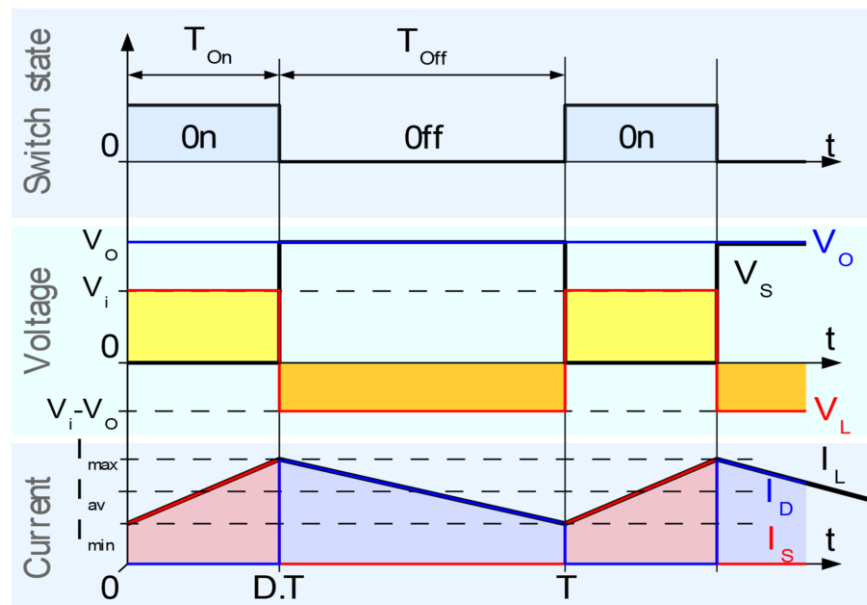


Figure (II.4). Waveform of a DC-DC Boost Converter.

We define the duty cycle as:  $D = \frac{T_{on}}{T}$

[0,  $T_{on}$ ]: The switch (S) is closed, the inductance current increasing progressively, the inductance stores up energy. The figure (II.5) presents the boost converter in the on time [20].

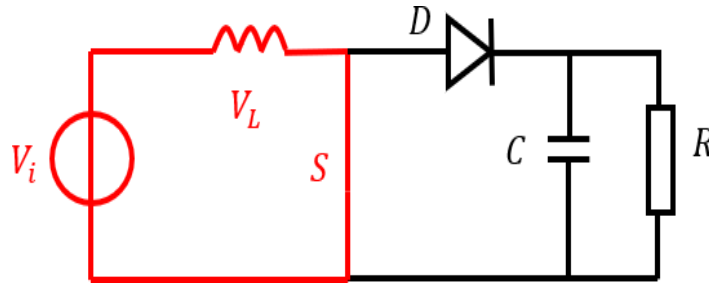


Figure (II.5). Boost Converter During on Time.

The voltage across the inductor is:

$$V_i = N_L \quad (II.6)$$

The mathematical equation characterizing the inductance current is given by:

$$\frac{dI_L}{dt} = \frac{V_i}{L} \quad (II.7)$$

[ $T_{on}$ ,  $T$ ]: The switch (S) is open, the inductance generates a voltage which is added to the source voltage, which is applied to the load (R) through the diode (D). The figure (II.6) presents the boost Converter during off time.

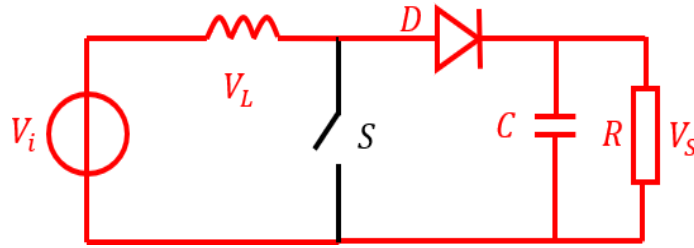


Figure (II.6). The Boost Converter During Off Time.

The voltage across the inductance is:

$$V_L = V_i + V_s \quad (II.8)$$

The mathematical equation characterizing the inductance current is given by:

$$\frac{dI_L}{dt} = \frac{V_i - V_s}{L} \quad (II.9)$$

The average value of the voltage  $V_L$  is zero:

$$\langle V_L \rangle = \int_0^T V_L dt = 0 \quad (II.10)$$

So:

$$\langle V_L \rangle = (V_i)(D * T - 0) + (V_i - V_s)(T - D * T) = 0 \quad (II.11)$$

Then:

$$V_s = \frac{V_i}{1-D} \quad (II.12)$$

With:

$$I_0 = I_i (1 - D) \quad (\text{II.13})$$

The design of the boost converter inductance depends essentially in the current ripple which is inversely proportional to the inductance value as shown in the next equation.

$$L = \frac{V_i * D}{\Delta I * f_{sw}} \quad (\text{II.14})$$

On the other side, some types of loads require an alternative voltage source, but the PV panel generates direct current, so, the direct connection is not possible in this case [20].

### II.3.3. DC/AC Converter

An inverter is a power electronics device that converts DC voltage into AC voltage. The structure of an inverter typically includes electronic switches such as IGBTs, power transistors, or thyristors. To generate an alternating signal of a specific frequency, the DC source is modulated using switches controlled by pulse width modulation (PWM) [23].

## II.4. MPPT Control Technique

### II.4.1 Definition

In a photovoltaic system consisting of a photovoltaic source and a load, the search for the optimal operating point through optimization techniques represents an important step. This control technique is often referred to in the literature as "Maximum Power Point Tracking, MPPT.

By definition, an MPPT control, associated with an intermediate adaptation stage, allows a PV generator to operate continuously at its maximum power. The performance of these controls depends on the speed of reaching the maximum power point, the way they oscillate around this point, and the robustness of the controller to abrupt atmospheric changes such as partial shading (PS) [24].

### II.4.2 Operating Principle of MPPT

The maximum power point tracker (MPPT) enables the photovoltaic module to operate at its maximum power point. The principle of MPPT control is to search for the maximum power point (MPP) while ensuring optimal adaptation between the generator and its load, thereby facilitating the transfer of maximum power.

The MPPT system is typically designed with a converter that regulates the power drawn from the solar panel. The maximum power point (MPP) is generally controlled by two variables: voltage and power. These variables are measured continuously and reused in a feedback loop to determine if the solar module is operating at the MPP.

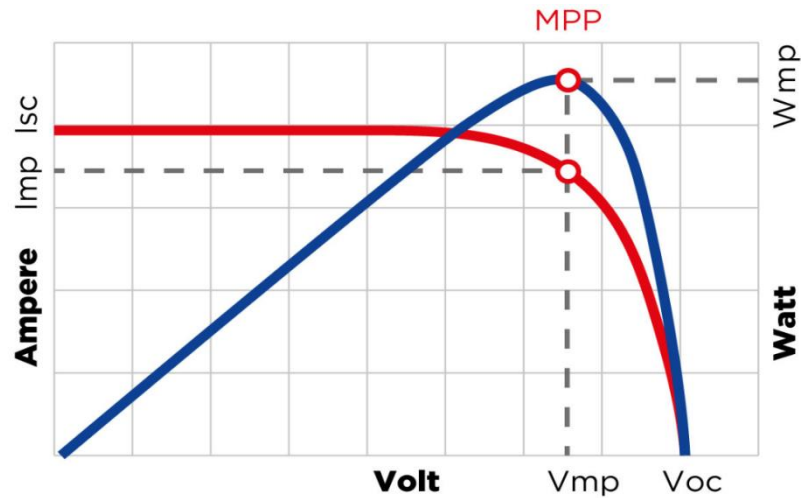


Figure (II.7). Principle of MPPT Control.

## II.5. MPPT Control Algorithms

The performance of a PV panel is influenced by meteorological conditions such as irradiance, temperature, air mass spectrum, and shadowing. To maximize the energy output from the solar panel, a step-down converter architecture is often employed. To achieve this objective, several maximum power point tracking (MPPT) control algorithms have been developed. Among the most popular are hill climbing-based techniques, which utilize the power-voltage characteristic curve. Notable examples of these techniques include "Perturb and Observe" (P&O) and "Incremental Conductance" (INC) [26].

### II.5.1 Perturbation and Observation (P&O) Method

The P&O method is the most popular MPPT algorithm due to its simplicity. It's one of the Hill climbing algorithms. The objective of this algorithm is to operate the system at its maximum power by incrementing or decrementing the voltage at the operating point and observing the effect of this perturbation on the power (figure II.8). The table (II.1) shows the response of the control system for each case [23]:

Table (II.1). The response of the control system for each case of P&O algorithm.

Case n°	$\Delta V$	$\Delta P$	$\frac{\Delta P}{\Delta V}$	Direction of tracking	Reponses of the control
1	+	+	+	Good	Incrementing: $V_{ref} = V_{ref} + V$
2	-	-	+	Bad	Incrementing: $V_{ref} = V_{ref} + V$
3	+	-	-	Bad	Decrementing: $V_{ref} = V_{ref} - V$
4	-	+	-	Good	Decrementing: $V_{ref} = V_{ref} - V$

Different cases are shown in the figure (II.8):

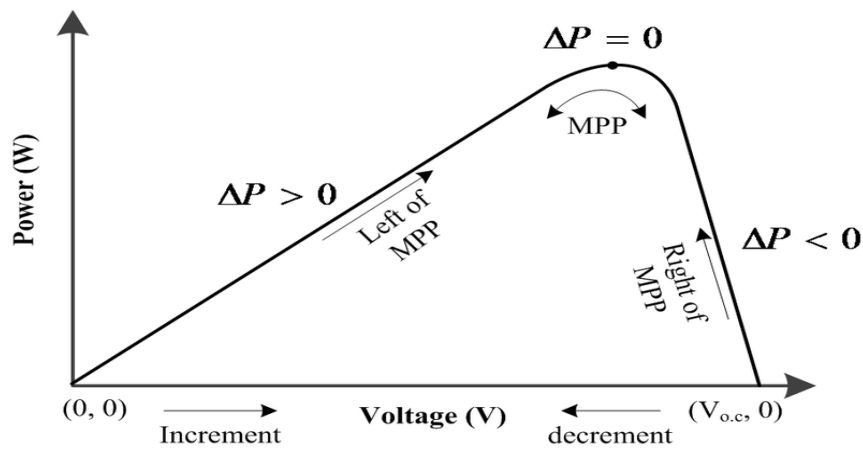


Figure (II.8). The Different Possible Cases for the Functioning of P&O Algorithm.

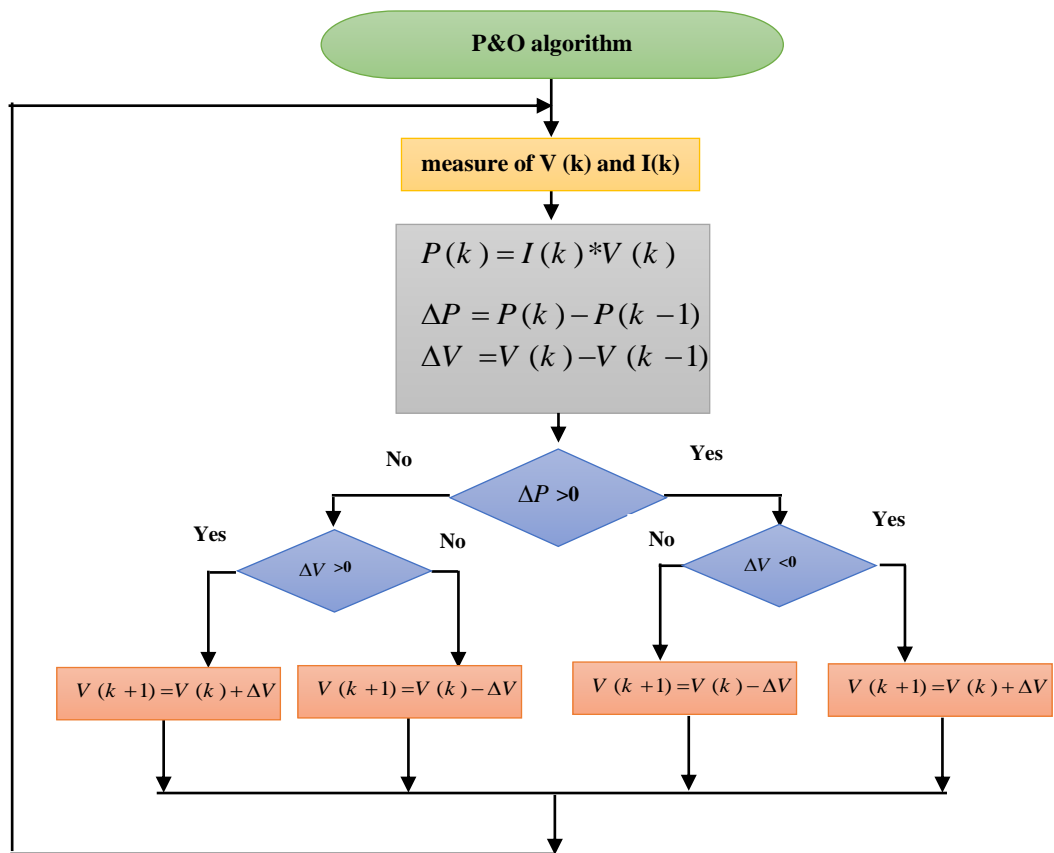


Figure (II.9). Flowchart of the P&O algorithm.

### II.5.2 Incremental Conductance (INC) Method

To track MPP, Incremental Conductance (INC) method utilizes the ratio of incremental conductance to instantaneous conductance value of the PV module. Based on this value, the slope of P-V characteristics is altered. In reference to the change in slope, duty cycle for converter is generated. For MPP tracking applying INC algorithm follows three common steps:

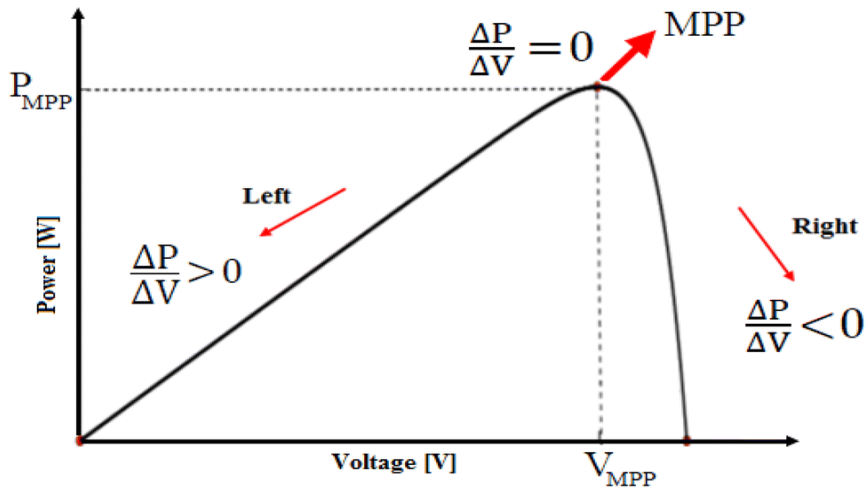


Figure (II.10). Concept of Incremental conductance algorithm

The flowchart for simple INC method is shown in Fig. (II.11). The researchers have followed many techniques to reduce the tracking error in INC method. [22]

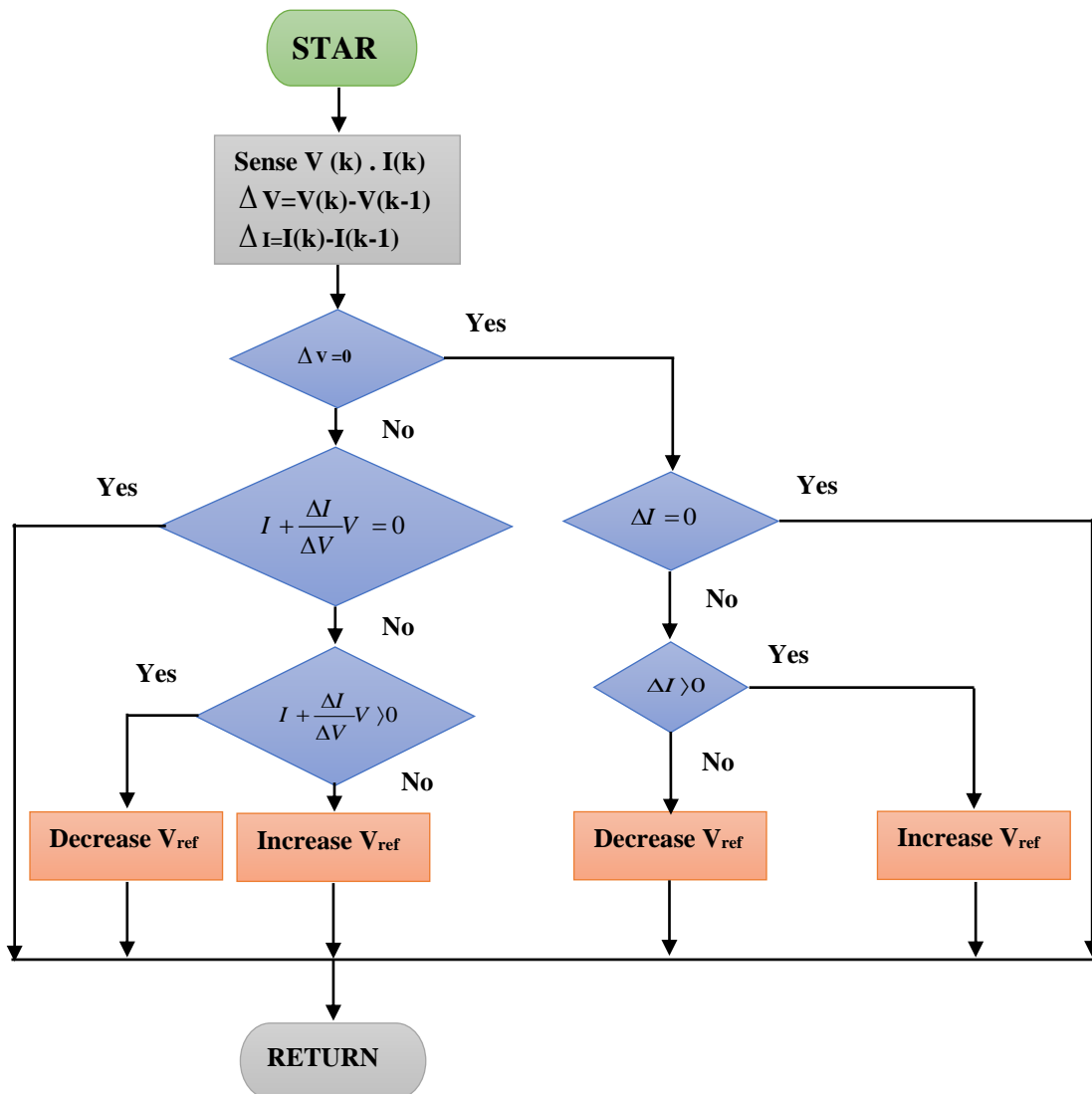


Figure (II.11). Flowchart of the Incremental Conductance (INC) algorithm.

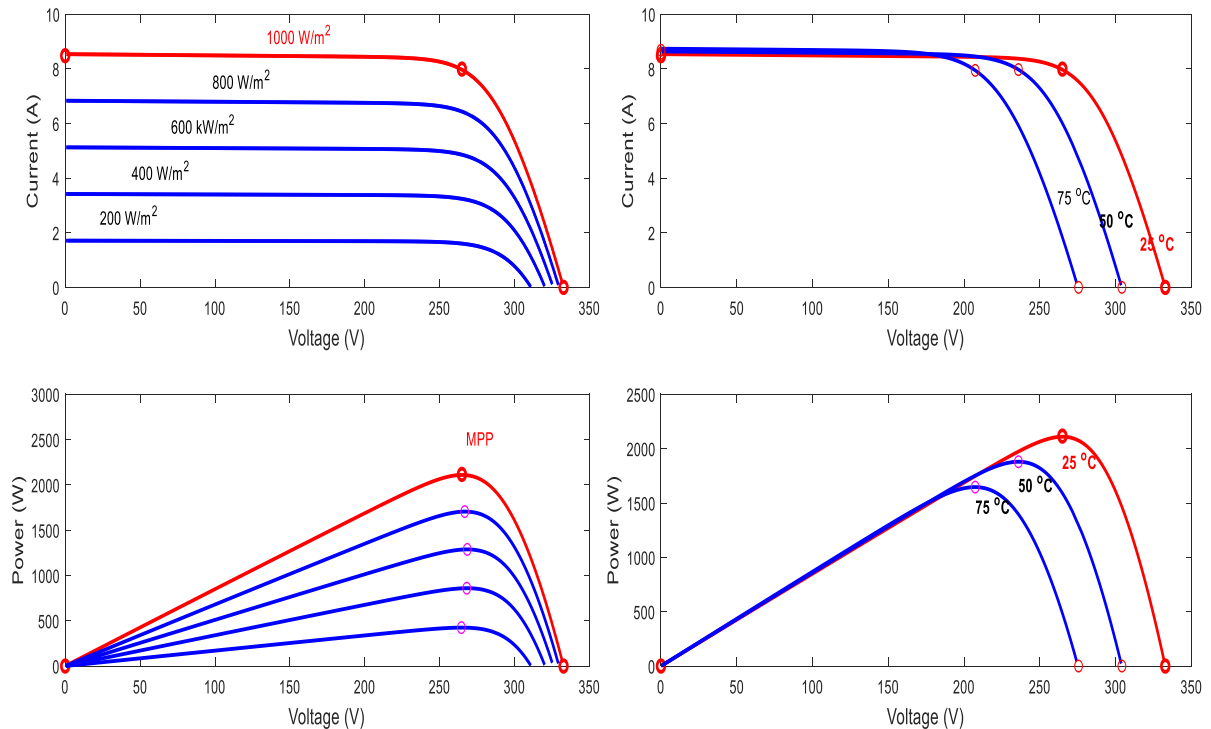
## II.6. Simulation Results

In this work, the photovoltaic PV array a 2.11 kW was constructed using nine solar panels connected in series ( $9.n_s$ ) and one parallel string ( $n_p$ ). The PV array model was based on the T5-SER-235P model from the *Matlab/Simulink* library. Table (II.2) presents the key characteristics of both the single solar panel and array PV model.

**Table (II.2): PV model characteristics.**

	PV	PV Array
Maximum power ( $P_{mpp}$ )	235 W	2115 W
Maximum current ( $I_{mpp}$ )	7.99 A	7.99 A
Maximum voltage ( $V_{mpp}$ )	29.42 V	264.78 V
Open circuit voltage ( $V_{oc}$ )	36.96 V	332.64 V
Short circuit current ( $I_{cc}$ )	8.48 A	8.48 A

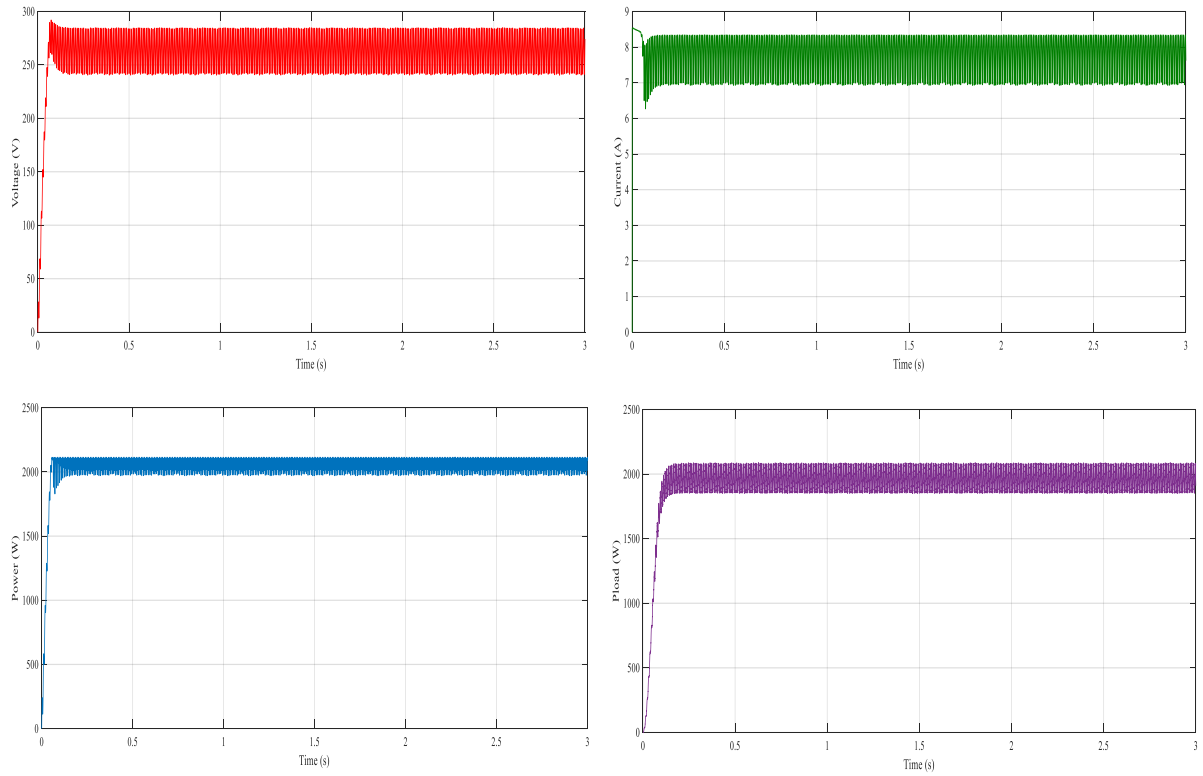
The figure (II.12) presents the current-voltage (I-V) and power-voltage (P-V) curves obtained from the PV panel Simulink model under various irradiance and temperature conditions. These curves illustrate the impact of changing environmental factors on the electrical behavior of the PV array. By analyzing the I-V and P-V curves, we can gain valuable insights into parameters like the maximum power point (MPP) voltage ( $V_{mpp}$ ) and current ( $I_{mpp}$ ), which are crucial for optimizing the PV system's performance.



**Figure (II.12).** I-V and P-V curves for PV array under various irradiance and temperature conditions

II.6.1. Standard Conditions ( $E=1000W/m^2$ ,  $T=25C$ )

❖ P&O Algorithm



❖ INC Algorithm

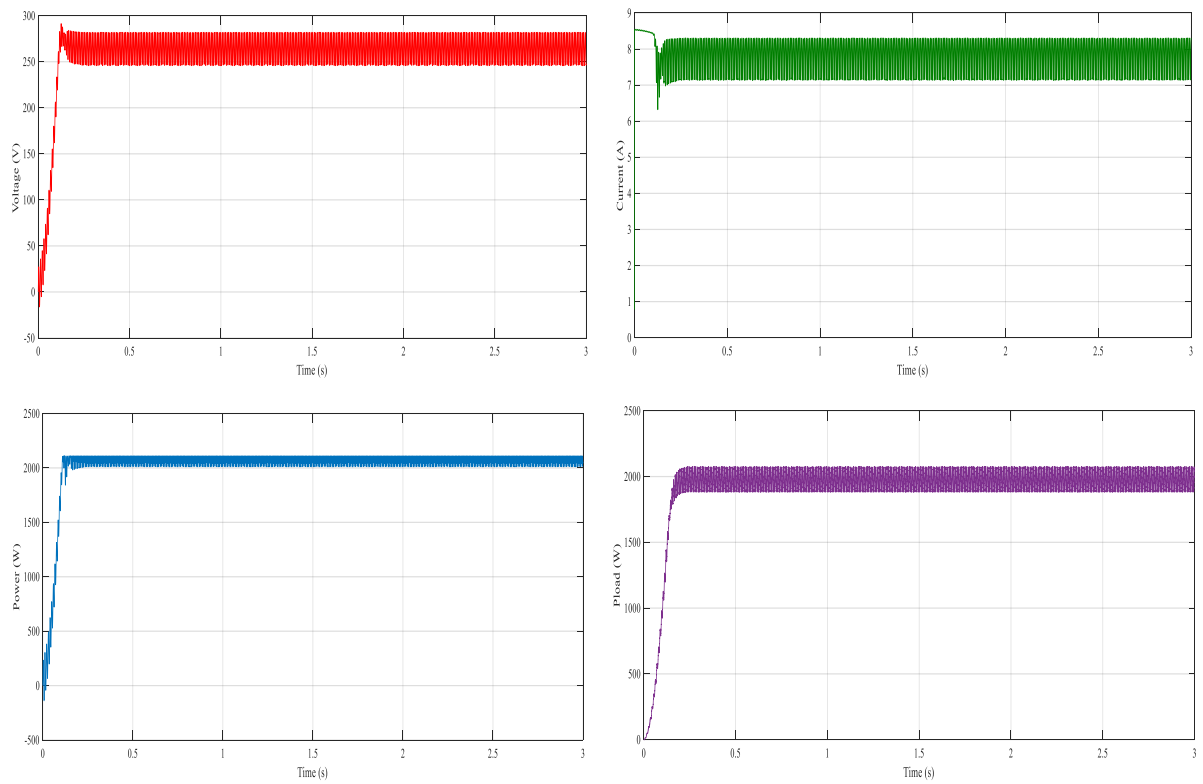


Figure (II.13). Simulation Results of the PV at ( $T=25^{\circ}C$ ,  $E=1000W/m^2$ )

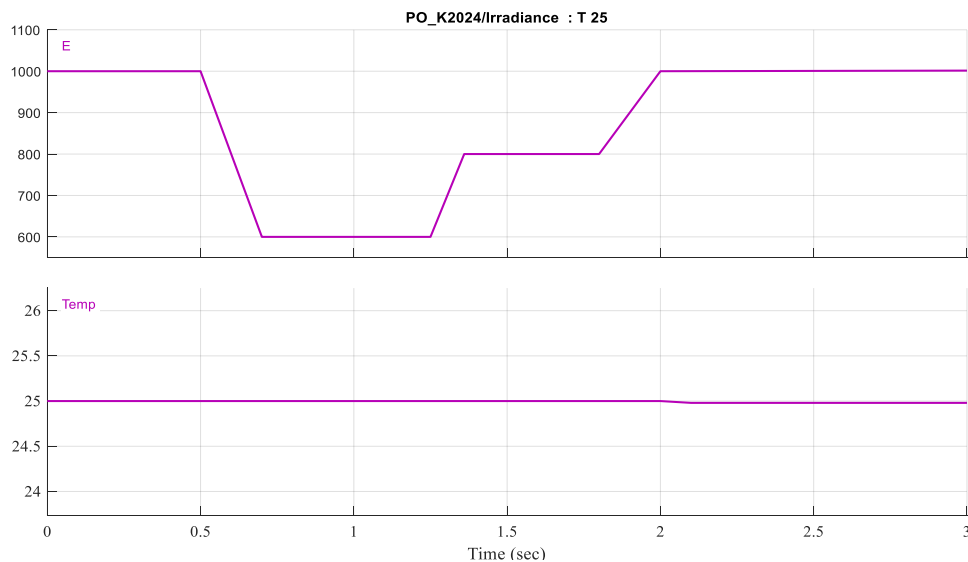
### • Interpretation of the results:

Under standard test conditions (STC) of  $1000 \text{ W/m}^2$  irradiance (E) and  $25^\circ\text{C}$  temperature (T), the simulation results demonstrate successful Maximum Power Point Tracking (MPPT) by both Perturb and Observe (P&O) and Incremental Conductance (INC) methods. This is evident from the observed power output: it increases until reaching the Maximum Power Point (MPP) and then stabilizes throughout the simulation.

Furthermore, the results highlight the boosting effect of the converter. The output voltage from the converter is consistently higher than the voltage provided directly by the photovoltaic (PV) module. Additionally, the INC method appears to exhibit a faster response time in reaching the MPP compared to the P&O method.

### II.6.2. Influence of Irradiance with Constant Temperature

The following figures represent the results of the PV panel for the contrast in the case of variable irradiance and constant temperature ( $T = 25^\circ\text{C}$ ):

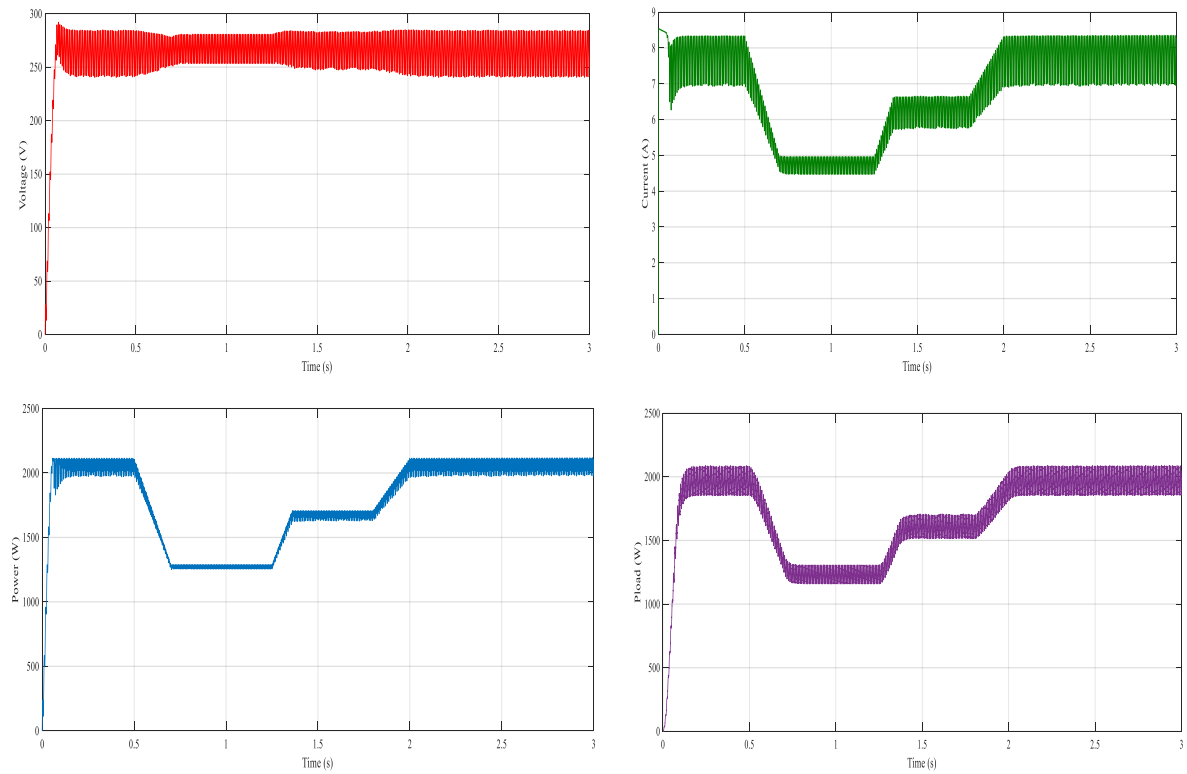


**Figure (II.14).** Signal Builder for Variable Illumination and Constant Temperature.

This section investigates the impact of varying irradiance levels on the performance of the PV panel while maintaining a constant temperature of  $25^\circ\text{C}$  (Fig.II.14). The figure (II.15) illustrate the simulation results obtained for both P&O and INC MPPT methods.

As evident from figures (II.15), a decrease in irradiance leads to a proportional reduction in both the output power and current of the PV panel. This phenomenon can be explained by the reduced availability of light energy for conversion into electricity at lower irradiance levels. Interestingly, the voltage exhibits a smaller decrease compared to power and current. The INC method exhibits minimal disturbance during the tracking process,

❖ P&O Algorithm:



❖ INC Algorithm

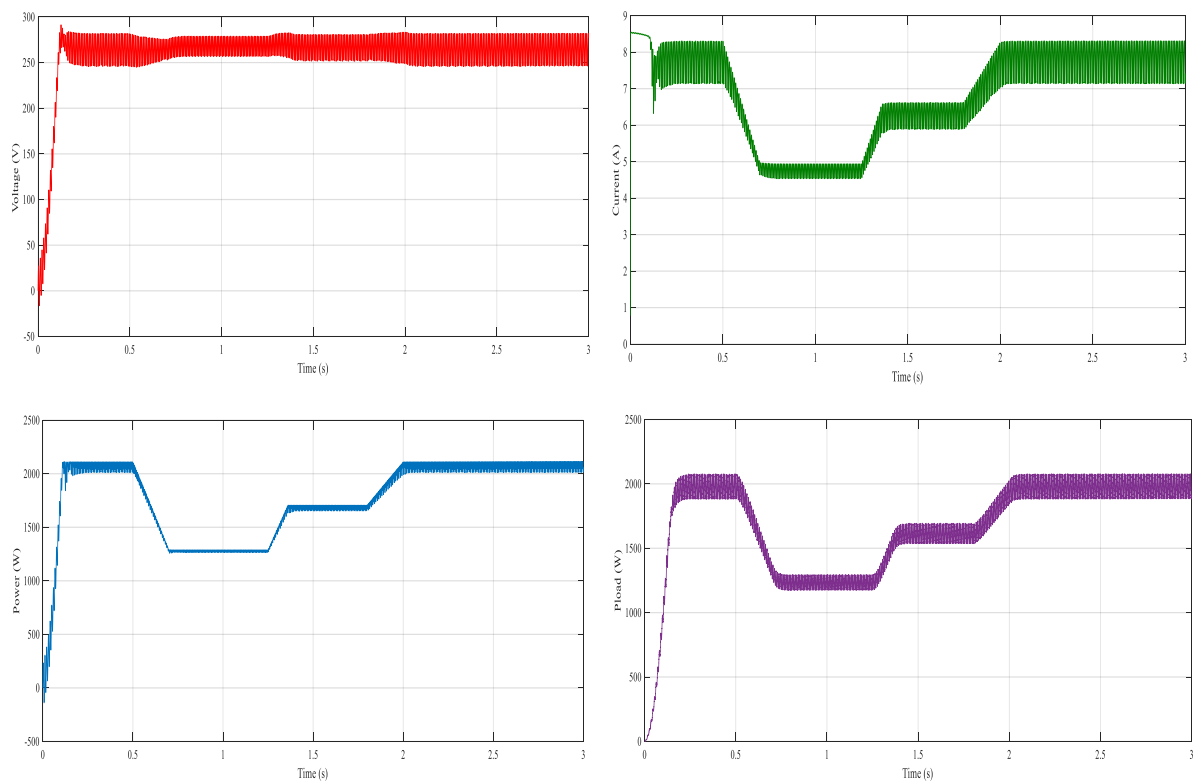
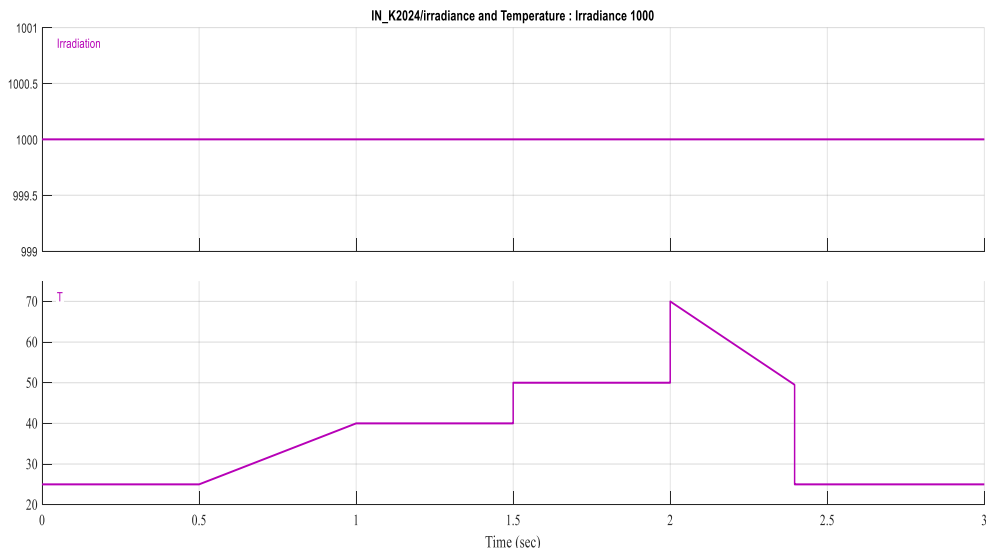


Figure (II.15). Simulation Results of the PV for Variable Irradiance and (T=25°C).

### II.6.3. Influence of Temperature with Irradiance Constant

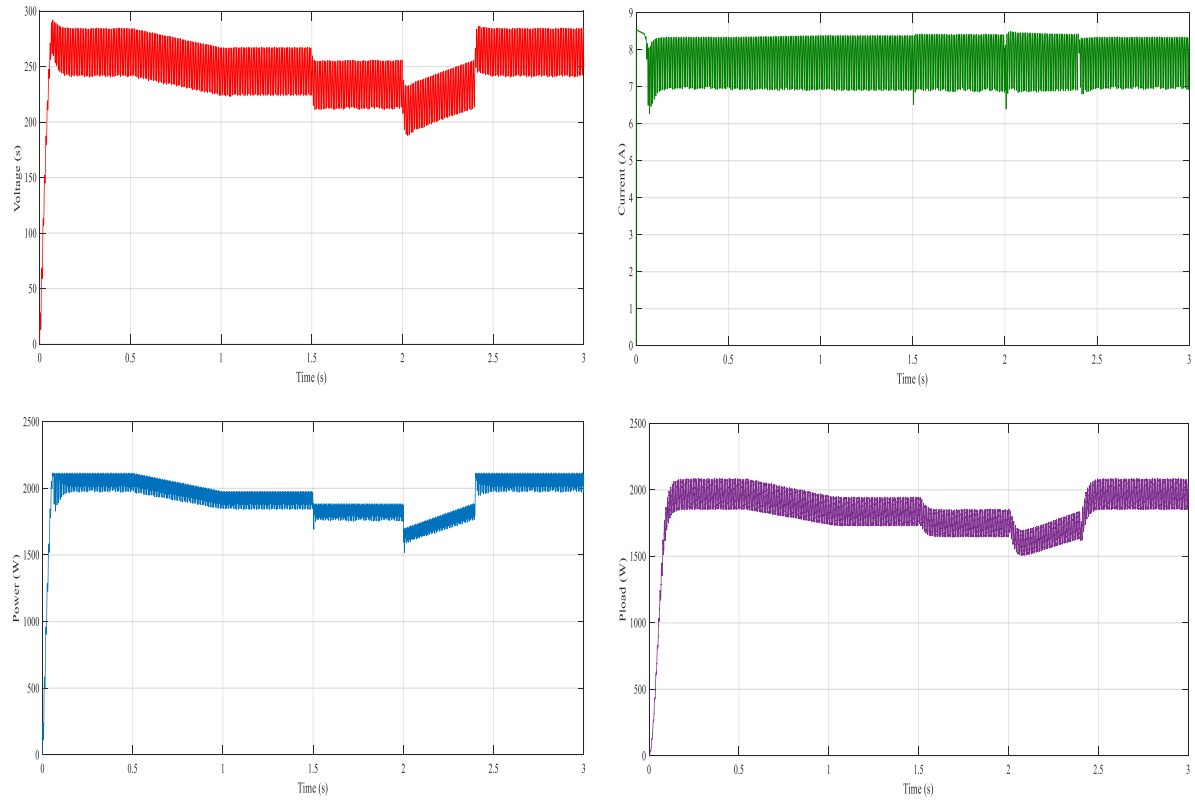
This section explores the impact of varying temperature on the performance of the PV panel while maintaining a constant irradiance of  $1000 \text{ W/m}^2$ . The following figure (II.17) illustrates the simulation results obtained for both P&O and INC MPPT methods.

As observed in the figure, an increase in temperature leads to a decrease in both the output voltage and power of the PV panel. This phenomenon can be attributed to the increased internal resistance of the panel at higher temperatures. Interestingly, the current exhibits a slight increase with rising temperature. However, this increase is typically outweighed by the decrease in voltage, resulting in a net reduction in power output. This behavior aligns with the well-established dependence of PV panel performance on temperature. The simulation results confirm the detrimental effect of temperature on the efficiency of PV panels.



**Figure (II.16).** Signal Builder for Variable Temperature and Constant Illumination.

❖ P&O Algorithm:



❖ INC Algorithm

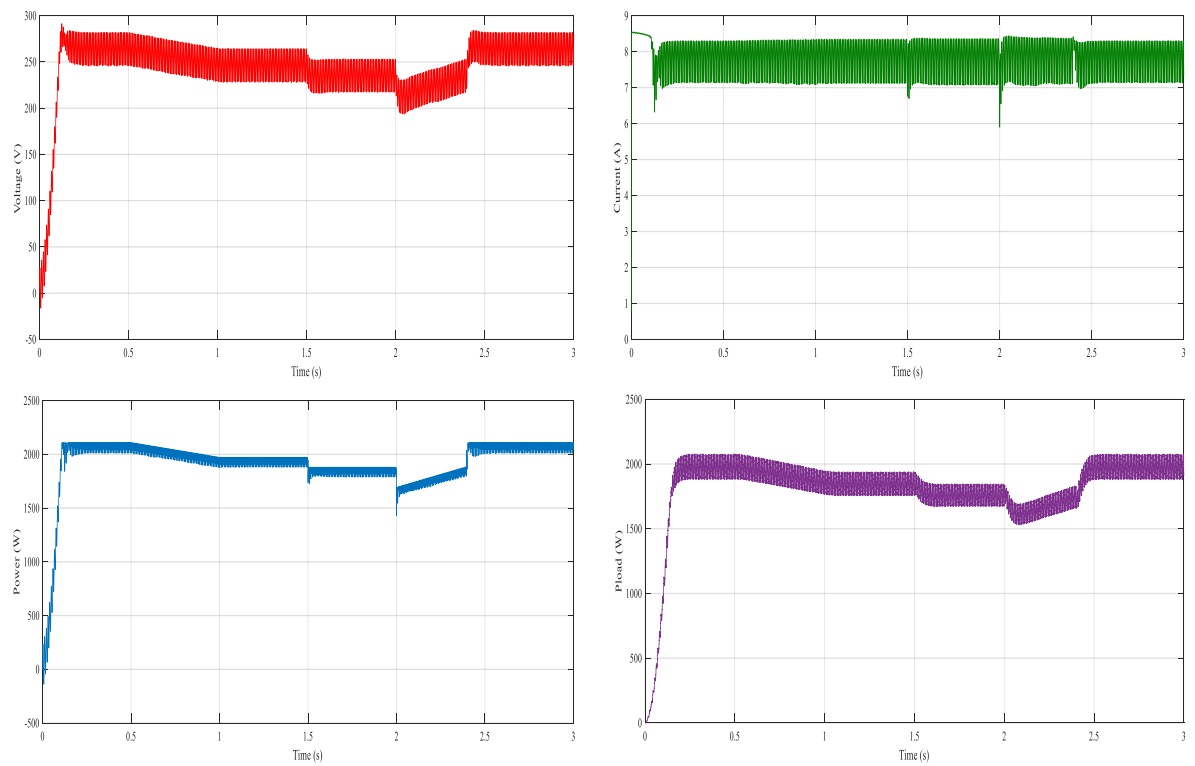


Figure (II.17). Simulation Results of the PV for Variable Temperatures and ( $E=1000W/m^2$ )

## II.7. Conclusion

This chapter delves into the world of Maximum Power Point Tracking (MPPT) techniques, a crucial aspect of optimizing photovoltaic (PV) system performance. MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (INC), play a vital role in ensuring the PV system operates at its peak efficiency. These techniques dynamically adjust system parameters to maintain the operating point of the solar panel at its Maximum Power Point (MPP) under varying environmental conditions. By constantly tracking the MPP, MPPT algorithms mitigate the negative impact of fluctuating irradiance and temperature, maximizing the power output of the PV system.

# **Chapter III**

## **Design and simulation of FLC**

# Chapter III.

## Design and Simulation of FLC-MPPT

### III.1. Introduction

One characteristic of human reasoning is that it is often based on imprecise or even incomplete data. Indeed, the knowledge we have about any system is generally uncertain or vague, either because we doubt its validity or because we have difficulty expressing it clearly. Therefore, there arose a need for a new type of reasoning that closely resembles human reasoning and can be treated mathematically rigorously.

Recently, fuzzy logic control (FLC) has been used in maximum power point tracking (MPPT) systems, offering the advantage of being robust and relatively simple to develop, without requiring exact knowledge of the model to be regulated.

This chapter embarks on a journey to unlock the potential of fuzzy logic control for achieving optimal Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. To equip you with the necessary knowledge, we'll commence by establishing a foundation in fuzzy logic principles. We'll then meticulously dissect the various stages involved in crafting a robust fuzzy controller, tailored specifically for the task of MPPT. Finally, the chapter will culminate in a comprehensive exploration of how fuzzy logic control can be effectively harnessed to maximize power extraction from PV systems under varying operating conditions.

### III.2. Application Domain

The approach to problem-solving using fuzzy logic differs from the one typically adopted in scientific endeavors. It is far more pragmatic than deterministic. Decision-making in fuzzy logic is based on the notion of expertise, which allows for quantifying fuzziness based on prior or previously acquired knowledge. The application domains of fuzzy logic in decision-making processes are evident in the following cases [28]:

- For complex systems where modeling is difficult or impossible;
- For systems controlled by human experts;
- When human observation leads to inputs or control rules;
- For systems with numerous continuous or discontinuous inputs/outputs;
- For MPPT control of photovoltaic systems.

### III.3. Principles and Definitions of Fuzzy Logic

#### III.3.1. Principle

The basic idea emerged when it was observed that programming an automaton to perform a task, seemingly simple for a human, proved challenging. Thus, the human mode of reasoning and the means to formalize human knowledge into a language understandable to a machine constitute the two main subjects of consideration that led to the emergence of fuzzy logic. Its implementation is now facilitated by the availability of dedicated microprocessors and powerful development tools. The concept of fuzzy logic arises from the recognition that the Boolean variable, which can only take two values (true or false), is poorly suited to represent most common phenomena. Indeed, classical logic considers a proposition to be either true or false. In contrast, fuzzy logic distinguishes an infinite number of truth values (between 0 and 1) [29].

#### III.3.2. Definitions

Fuzzy Sets: In binary logic, the membership function  $\mu_A$  characterizing the membership of an element  $x$  from the universe of discourse  $X$  to a classical set  $A$  only takes values 0 and 1.

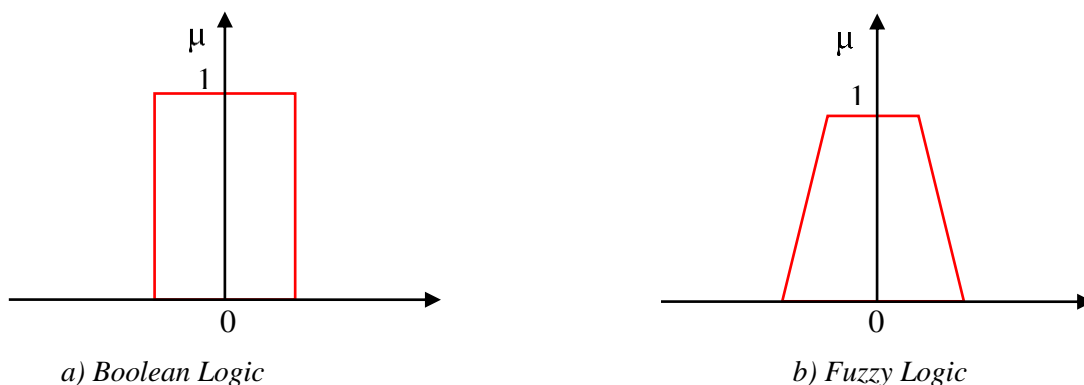
$$\mu_A : X \rightarrow \{0, 1\} \quad (\text{III.1})$$

A fuzzy set can be viewed as a generalization of the concept of a classical set. In the theory of fuzzy sets, the values of the membership function  $\mu_A(x)$  are within the interval  $[0, 1]$ :

$$\mu_A : X \rightarrow [0, 1] \quad (\text{III.2})$$

This fuzzy set  $A$  can be represented as a set of ordered pairs (degree of membership):

$$A = \{(x, \mu_A(x)) / x \in A\} \quad (\text{III.3})$$



**Figure (III.1).** Membership characteristic function for Boolean logic and fuzzy logic.

Another form of A can be expressed as:

$$\begin{cases} A = \int_x \frac{\mu_A(x)}{x} & \text{if } X \text{ is continuous} \\ A = \sum_{j=1}^n \frac{\mu_A(x_j)}{x_i} & \text{if } X \text{ is discrete} \end{cases} \quad (\text{III.4})$$

- **Support:** The support of the fuzzy set F is the numerical set of all points u in X such that  $\mu_A(x) > 0$ .
- **Crossing Point:** A crossing point is defined as an element u of X such that  $\mu_A(x) = 0.5$
- **Fuzzy Singleton:** If the support of the fuzzy set contains only one point  $x \in X$  such that  $\mu_A = 1$ , It is called a fuzzy singleton.
- **Linguistic Rule Notions**
  - Descriptions of certain situations, phenomena, or processes generally involve fuzzy expressions such as: Hot, cold, fast, slow, Large, small, ...etc.
  - Expressions of this kind constitute the values of linguistic variables in fuzzy logic. Systems based on fuzzy logic typically utilize human knowledge in the form of "if-then" rules.

### III.3.3. Operations on Fuzzy Sets

• **ZADEH MIN/MAX Operators:** Let A and B be two fuzzy sets in X with membership functions  $\mu_A$  and  $\mu_B$  respectively. The union, intersection, and complement of fuzzy sets are derived using their membership function.  $\mu_A(x)$  et  $\mu_B(x)$  In classical set theory, we define the intersection, union of fuzzy sets, as well as the complement of a fuzzy set. These relations are translated by the operators "and", "or", and "not".

• **Complementation (operator "not"):** The membership function of the complement of a set. The "not" operator is realized by:

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \quad (\text{III.5})$$

• **Intersection (operator "and"):** The intersection of two fuzzy sets A and B in X is the fuzzy set consisting of elements of X affected by the smallest of their two membership degrees. It can be realized by: The "Min" function:

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)] \quad (\text{III.6})$$

• **Union (operator "or"):** The union of two fuzzy sets A and B in X is the fuzzy set consisting of elements of X affected by the largest of their two membership degrees. It can be realized by: The "Max" function:

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)] \quad (\text{III.7})$$

The figure (III.2) summarizes these operations graphically: [29]

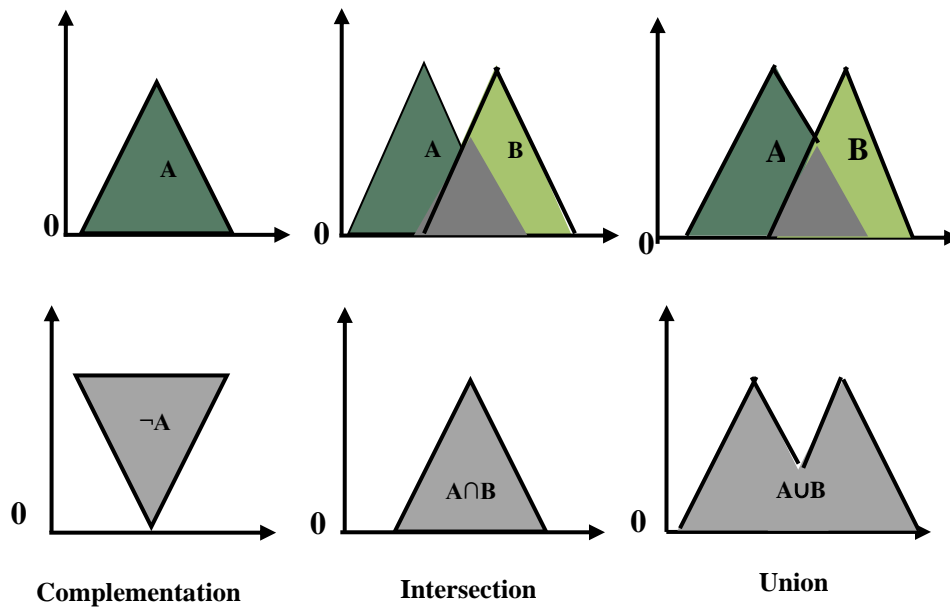


Figure (III.2). Example of operations on fuzzy sets.

### III.3.4. Fuzzy Implication

Consider a fuzzy rule of the form "if V is A then W is B", constructed from two linguistic variables (V, X, TV) and (W, Y, TW). Fuzzy implication is an operator that evaluates the degree of truth between the elementary fuzzy propositions "V is A" and "W is B" based on the values of the premise on one hand, and those of the conclusion on the other hand.

$$\mu_R(x, y) = \text{imp}(\mu_A(x), \mu_B(x)) \quad (\text{III.8})$$

To determine the degree of truth of the fuzzy proposition, we need to define fuzzy implication. The most commonly used operators in fuzzy control are the MAMDANI and LARSEN implications. [30]

- MAMDANI Implication:

$$\mu_R(x, y) = \text{MIN}(\mu_A(x), \mu_B(x)) \quad (\text{III.9})$$

- LARSEN Implication:

$$\mu_R(x, y) = \mu_A(x) \cdot \mu_B(x) \quad (\text{III.10})$$

### III.3.5. Membership Functions

A definition of linguistic variables using membership functions is necessary in order to process fuzzy reasoning by computer. Most commonly, we use the following functions for membership functions [30]:

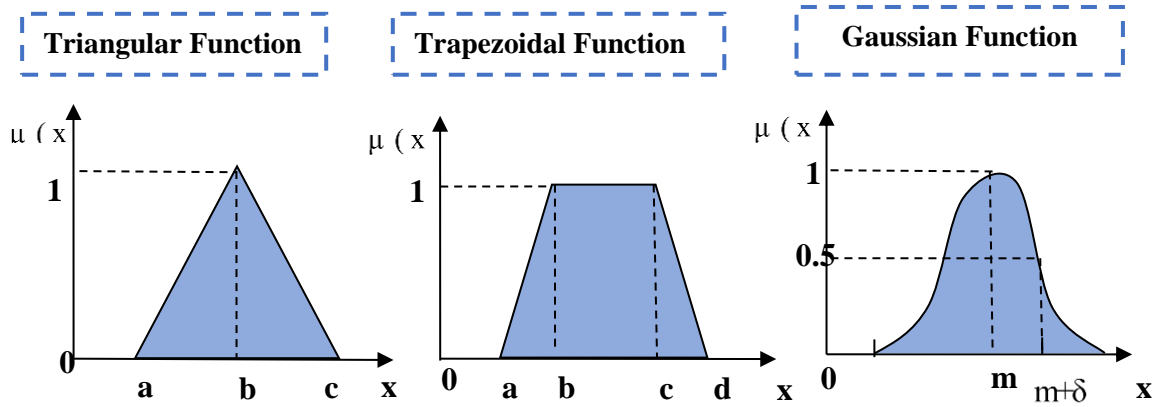


Figure (III.3). Typical membership functions.

### III.4. Design of Fuzzy Logic Controller Parameters

#### III.4.1. PV with MPPT based FLC

Figure (III.4) illustrates the basic diagram of a fuzzy logic based maximum power point tracker (FLC-MPPT). It can be seen from the observation that the only two state variables are sensed as inputs of fuzzy controller; output voltage and output current of PV module ( $V_{pv}$ ) and ( $I_{pv}$ ).

The fuzzy logic controller, from measurements, gives a signal proportional to the converter duty cycle ( $D$ ) which is fed to the converter through a pulse width modulator. This modulator drives the value of  $D$  to perform Pulse Width Modulation (PWM) that generates the control signals for the converter switch ( $s$ ). The fuzzy logic controller scheme is defined a closed loop system [31].

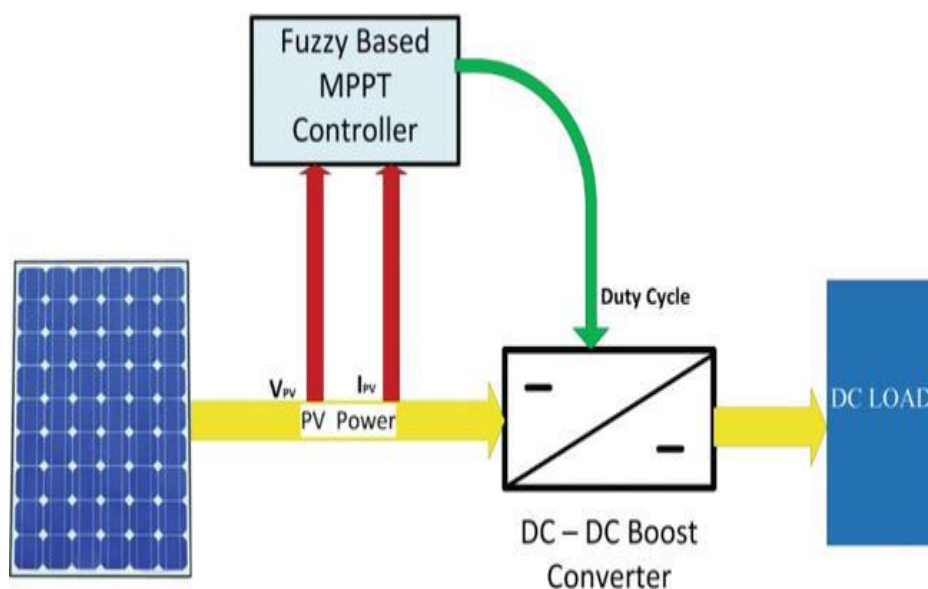


Figure (III.4). MPPT-Fuzzy control scheme for a maximum power point tracker.

### III.4.2 Fuzzy Logic Control

Fuzzy logic control is considered an important technique in industrial engineering application because it has a high ability to work with nonlinear system. It deals with imprecise and noisy input information based on a mathematical model in order to imitate human-like decisions in control implementation. This technique supports two types of fuzzy software system; Mamdani and Sugeno. The main structure of FLC includes three stages: fuzzification, fuzzy rules and defuzzification. A general block diagram of the FLC technique is shown in Figure (III.5) [32].

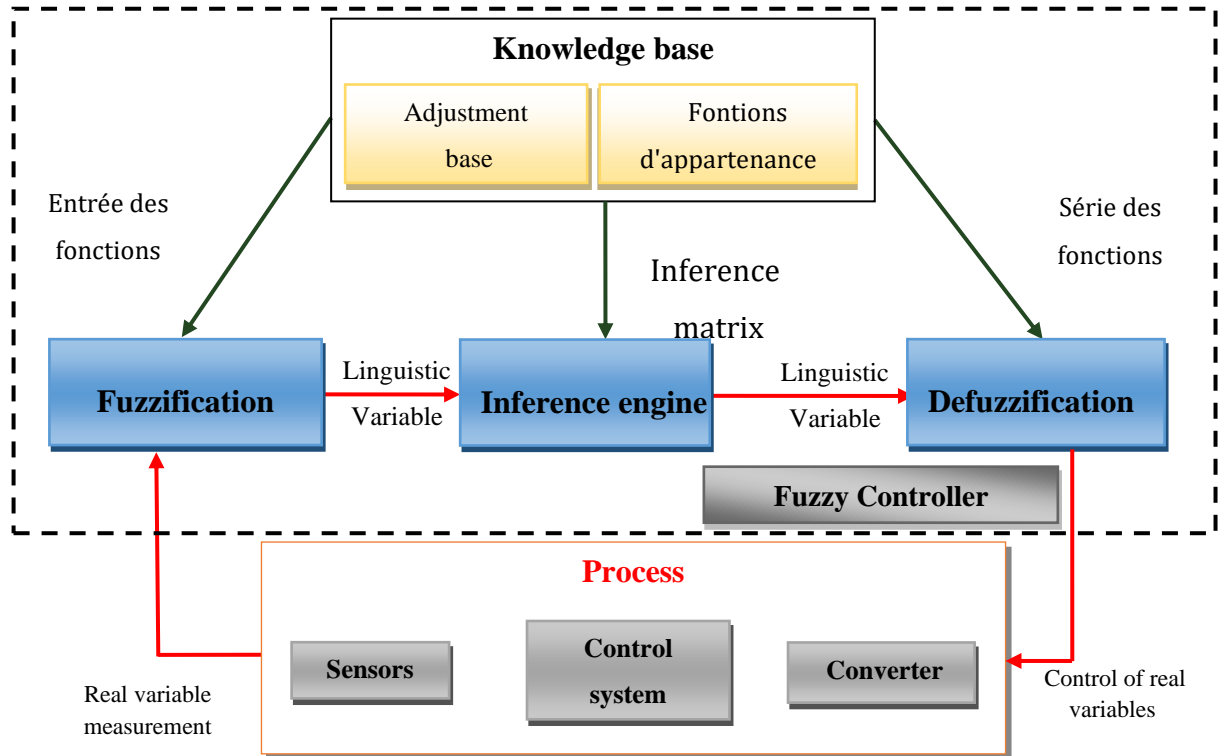


Figure (III.5). General diagram of fuzzy logic system.

## III.5. Application of Fuzzy Controller for MPPT Control

### III.5.1. Fuzzification

Based on the maximum power point relationship ( $\Delta P/\Delta V=0$ ), the fuzzy controller has two inputs. The first one is the variation of power with respect to voltage, denoted as the error  $E$ . The second one is the variation  $\Delta E$ , which represents the direction and speed of convergence. The output  $\Delta D$  is the variation of the duty cycle of the DC/DC converter.

The two controller inputs are defined by the following equations:

$$\mu_c(x) = \max\{\mu_a(x), \mu_b(x)\} \quad (III.11)$$

$$\Delta E(t) = E(t) - E(t-1) \quad (III.12)$$

The input variables E and CE are defined by linguistic terms; Negative Large (NL), Zero Error (ZE), Positive Large (PL).

The output variable D is partitioned into several classes for more precision; Negative Small (NS), Negative Large (NL), Zero Error (ZE), Positive Large (PL), Positive Small (PS).

The membership functions are represented by the following figure. To simplify our example, we use triangular membership functions.

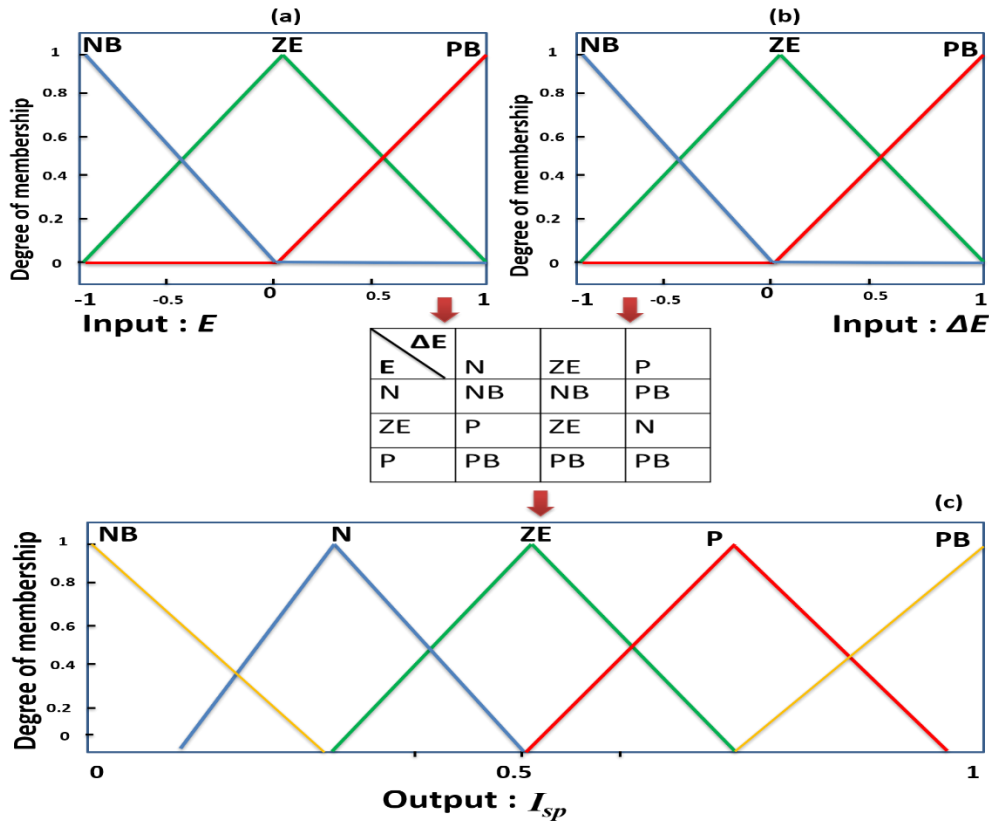


Figure (III.6). Characteristics of the basic fuzzy logic model.

### III.5.2. Inference

Consists of defining a logical relationship between the inputs and the output, using rules of the type IF... AND... THEN, for example: IF E is Positive Large AND CE is Zero THEN D is Positive Small. This means that:

If the operating point is far from the maximum power point (MPP) towards the left side, and the change in the slope of the P(V) curve is approximately zero; Then increase the duty cycle significantly to reach the MPP [16]. The figure (III.7) illustrates the principle of MPPT with fuzzy logic.

For the different inference methods, the MAX-MIN method is the most commonly used for this control. It involves using the MIN operator for AND and the MAX operator for OR.

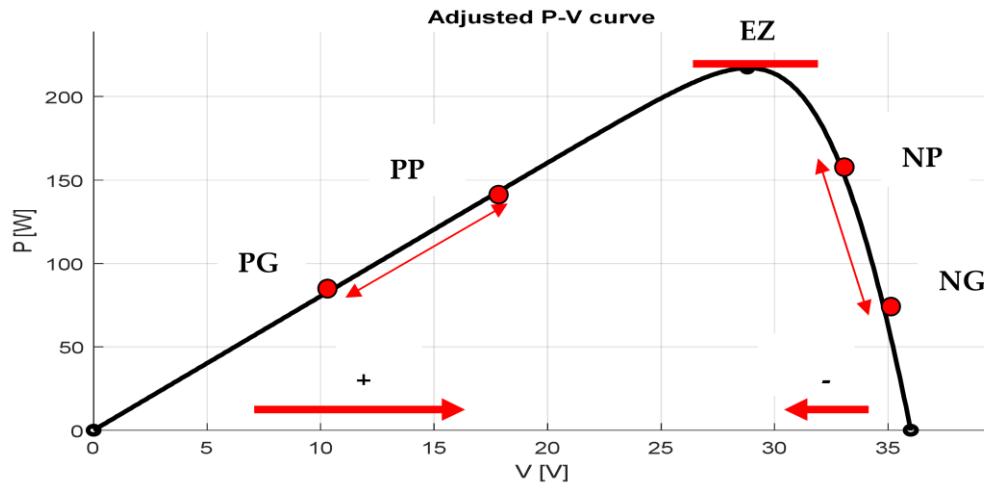


Figure (III.7). Fuzzy MPPT Principle.

### III.5.3. Defuzzification

Defuzzification is known as the process of conversion of fuzzy quantity into crisp quantity. There are many methods available for Defuzzification. The most common one is centroid method, which illustrated by the following formula:

$$\frac{\int (\mu(x)x)dx}{\int \mu(x)dx} \quad (III.13)$$

Where  $\mu$  is the membership degree of output  $x$ .

## III.6. Membership functions of the Proposed Fuzzy System

### III.6.1 Derivation of Control Rules

Fuzzy control rules are extracted by analyzing the system behavior. The different operating conditions are considered in order to improve tracking performance in terms of dynamic response and robustness. The algorithm can be explained as follows: The tracking process is started with an initial duty cycle,  $D=0$ . The converter input current  $I_m$ , and voltage  $V_m$ , are then measured and sense the duty cycle that can give maximum power output of the converter at that time based on predicted values that have already been entered into fuzzy system.

This operation repeats itself continuously until the power reaches the maximum value and the system becomes stable.

### III.6.2 Tuning of Control Rules

The fuzzy rules of the proposed system have been derived from the system behavior and tested in Simulink/MATLAB. Table (III.1).

Table (III.1). Fuzzy controller rules.

Current/Voltage	Small	Medium	High
Small	H	H	M
Medium	H	H	M
High	M	M	M

The rules in the table above are read as:

- 1- If (current is small) AND (voltage is small) then (MD is high).
- 2- If (current is small) AND (voltage is medium) then (MD is high).
- 3- If (current is small) AND (voltage is high) then (MD is medium).
- 4- If (current is medium) AND (voltage is small) then (MD is high).
- 5- If (current is medium) AND (voltage is medium) then (MD is high).
- 6- If (current is medium) AND (voltage is high) then (MD is medium).
- 7- If (current is high) AND (voltage is small) then (MD is medium).
- 8- If (current is high) AND (voltage is medium) then (MD is medium).
- 9- If (current is high) AND (voltage is high) then (MD is medium).

Where MD is duty cycle that represents the output of fuzzy controller.

### III.7. Advantages and Disadvantages of Fuzzy Logic Control

#### ❖ Advantages

- No need for system modeling.
- Ability to incorporate linguistic knowledge of the process operator.
- Ability to control complex systems (nonlinear and difficult-to-model systems).
- Availability of efficient development systems, whether through microprocessors, PCs, or integrated circuits.

#### ❖ Disadvantages

- Lack of precise guidelines for designing a control system (choice of measured variables, determination of fuzzification, inferences, and defuzzification).
- Artisanal and asymptotic approach (implementation of operator knowledge is often challenging).
- Inability to demonstrate the stability of the control circuit in all circumstances (in the absence of a valid model).
- Unassured consistency of inferences (possibility of contradictory inference rules).

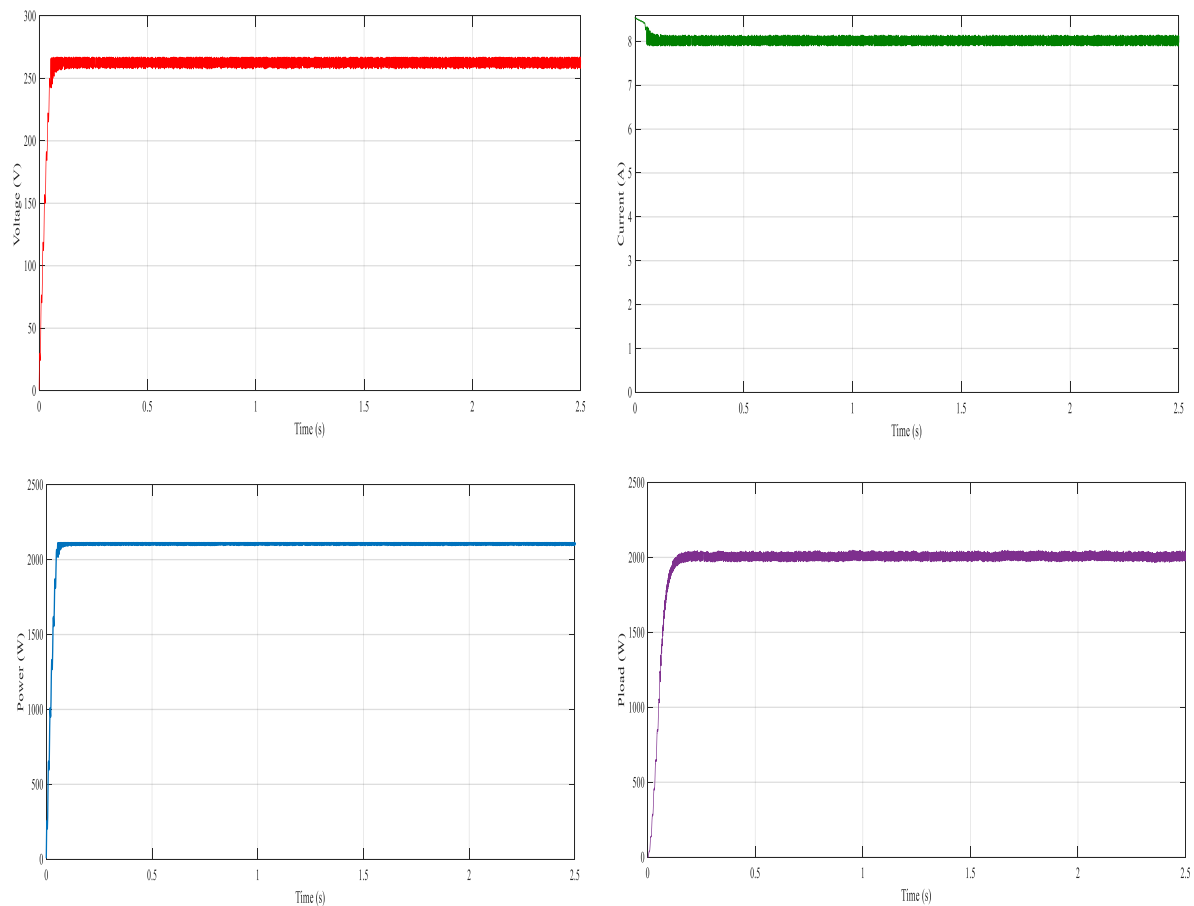
### III.8. Simulation of FLC-PV

#### 1. Fixed Profile: Standard Conditions

The simulation was conducted under STC of  $1000 \text{ W/m}^2$  irradiance and  $25^\circ\text{C}$  temperature to evaluate the effectiveness of the Fuzzy Logic Control (FLC) based MPPT method in extracting the optimal power from the PV array.

The results confirm successful Maximum Power Point Tracking (MPPT) by the FLC-MPPT method under STC conditions. As observed, the output power of the PV panel increases until reaching the Maximum Power Point (MPP) and then stabilizes throughout the simulation. This behavior indicates that the FLC algorithm effectively tracks the MPP, ensuring the system operates at its peak efficiency.

Figure (III.8) specifically showcases the effectiveness of the FLC algorithm. The fuzzy logic control signal clearly reaches and converges to the maximum power value of approximately  $2115 \text{ W}$ . This convergence demonstrates the robustness of the FLC-MPPT method in achieving optimal power extraction under standard conditions.



**Figure (III.8).** Simulation Results of the PV at ( $T=25^\circ\text{C}$ ,  $E=1000\text{W/m}^2$ ).

## 2. Variable Profile: Variable Irradiation and Constant Temperature

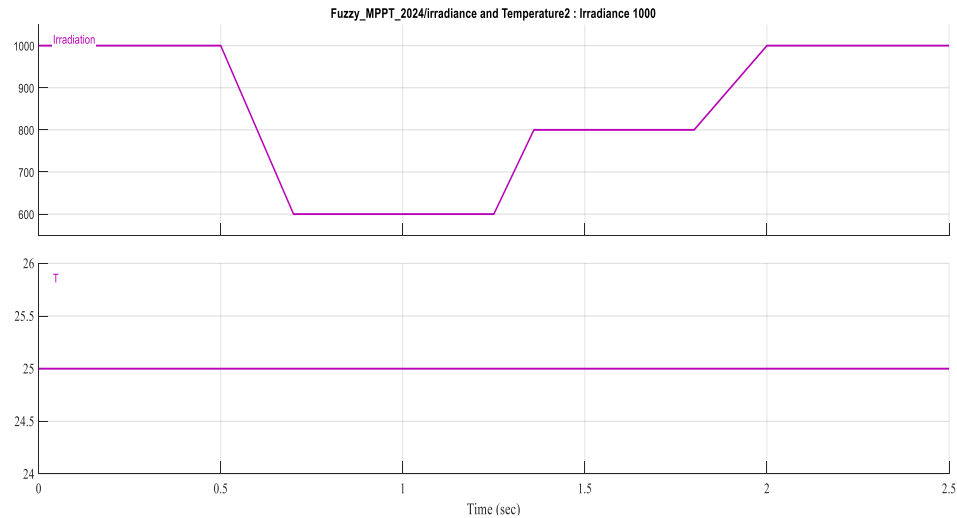


Figure (III.9). Variation of irradiance with constant temperature

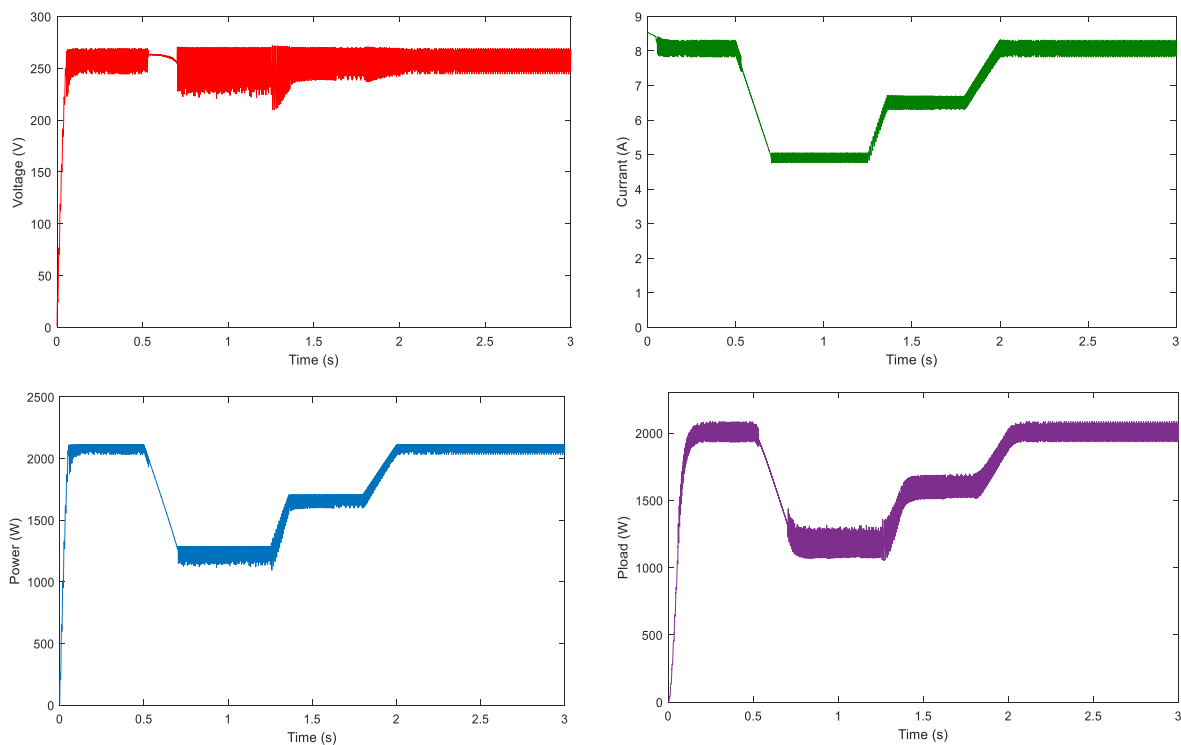


Figure (III.10). Simulation results of the PV for variable irradiance and ( $T=25^{\circ}\text{C}$ ).

This section investigates the performance of the FLC based MPPT algorithm under varying irradiance levels while maintaining a constant temperature of  $25^{\circ}\text{C}$ . Figure (III.10) presents the characteristic curves of the photovoltaic (PV) panel. The investigation utilizes a variable irradiance profile, as shown in figure (III.9). Evaluating the FLC-MPPT's ability to track the Maximum Power Point (MPP) under these dynamic conditions is crucial.

As expected, the voltage, current, and power output curves exhibit a proportional relationship with the irradiance profile.

This signifies the effectiveness of the FLC-MPPT algorithm in adjusting system parameters to adapt to changing irradiance levels. A decrease in irradiance leads to a corresponding decrease in the output voltage, current, and consequently, the photoelectric energy produced by the PV system. The negligible oscillations observed in the power curve highlight the efficient tracking of the MPP by the proposed control scheme under varying radiation levels.

### 3. Variable Profile: Variable Temperature and Constant Irradiance

We conducted our experiments by applying a variable temperature to our system, as shown in figure (III.16), and a fixed irradiance of  $E=1000 \text{ W/m}^2$ .

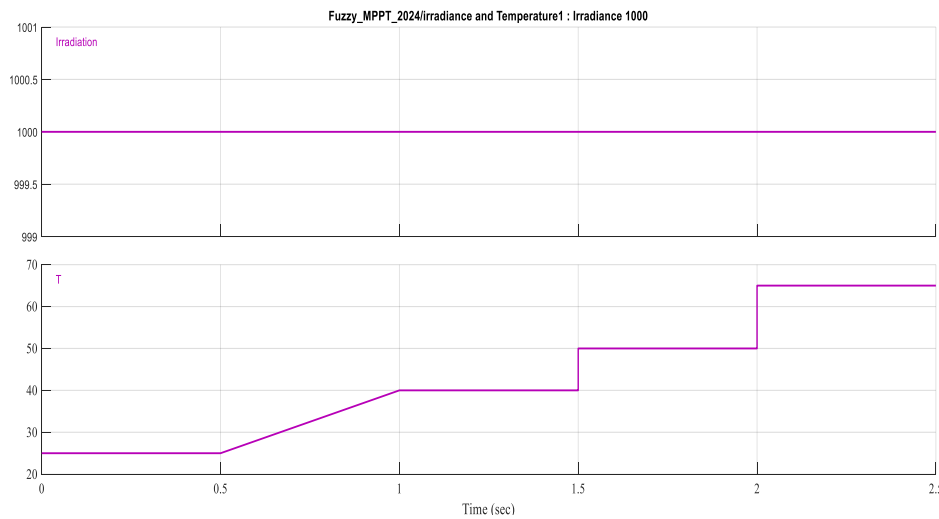


Figure (III.11). Temperature variation and Fixed Irradiance.

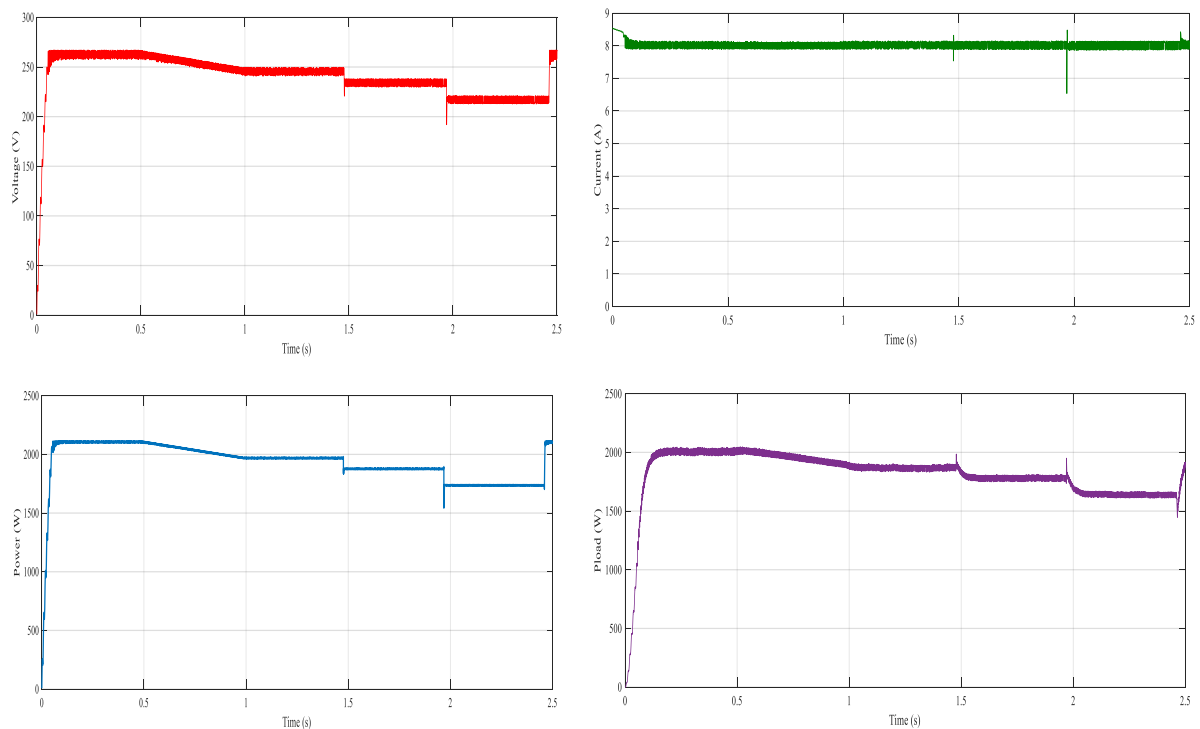


Figure (III.12). Simulation Results of the PV for Variable Temperatures and ( $E=1000\text{W/m}^2$ ).

The simulation results obtained under variable temperature with constant irradiance, figure (III.11) provide valuable insights into the performance of the FLC-MPPT algorithm.

The effectiveness of the FLC-MPPT algorithm in maintaining MPP tracking under variable temperature can be assessed by analyzing the stability of the power output curve, figure (III.12). The output power curve exhibits an inverse relationship with the temperature profile. This can be attributed to the inherent characteristic of PV panels where increasing temperature leads to a decrease in their efficiency. Observing minimal deviations from the peak power point signifies successful MPP tracking by the FLC method.

### III. 10. Conclusion

Fuzzy logic control (FLC) has emerged as a powerful tool in various fields, including electronics, control systems, and automation. Its ability to effectively handle imprecise, uncertain, and subjective information makes it particularly well-suited for addressing complex optimization problems like Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems.

This chapter delves into the concepts of fuzzy logic control, specifically tailored for understanding and designing a fuzzy MPPT controller. By leveraging the strengths of FLC, to develop a robust and adaptable MPPT solution for maximizing the power output of PV systems under dynamic operating conditions. Traditional MPPT techniques may struggle with the inherent variability and non-linearity of PV panel characteristics. Fuzzy logic offers several advantages in this context:

- Robustness: FLC can handle uncertainties in the PV system, such as fluctuating irradiance and temperature, without requiring precise mathematical models.
- Adaptability: Fuzzy logic controllers can adapt their behavior based on real-time operating conditions, ensuring optimal performance under varying environmental conditions.

**Chapter IV**  
**MPPT Based on**  
**Artificial Neural**  
**Networks**

# Chapter IV.

## MPPT Based on Artificial Neural Networks

### IV.1. Introduction

This chapter explores Artificial Neural Network (ANN) algorithms, a modern Maximum Power Point Tracking (MPPT) technique inspired by biological nervous systems. Building upon the algorithms presented in Chapter 1, this chapter delves into the theoretical underpinnings of Neural Networks, their application in MPPT-ANN, and the implementation process within a system. Finally, a comparison between the ANN approach and traditional MPPT methods will be presented.

### IV.2 Neural Network theory

Before using the network, several steps must be followed to validate and test the network as shown in the next sections [34].

#### IV.2.1 Neural Network definition

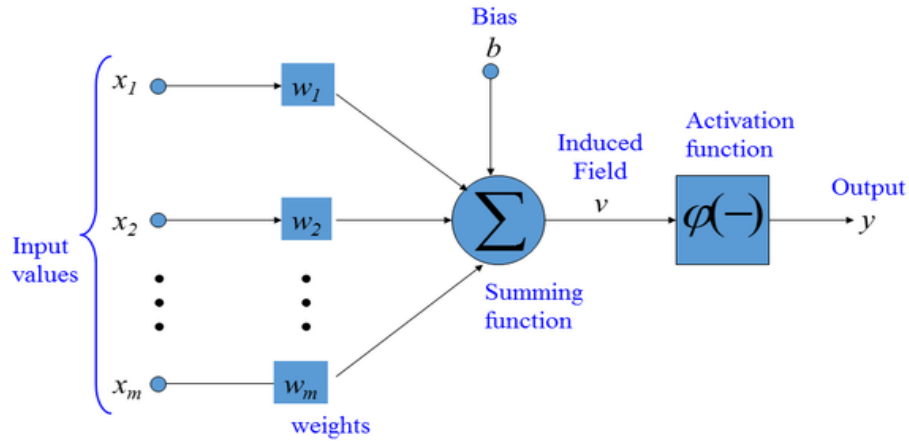
The term "neural networks" encompasses a range of models that aim to replicate some functionalities of the human brain by mimicking its basic structures. Over the past decade, artificial neural networks have seen a surge in application across various disciplines, including economics, ecology, biology, medicine, and more.

The artificial neural networks excel at solving problems like classification, prediction, categorization, optimization, pattern recognition, and associative memory. In data processing, they provide a powerful method for approximating complex systems, particularly when these systems defy modeling using traditional statistical methods.

Furthermore, neural networks are well-suited for scenarios involving non-linear relationships between input and output variables. Their inherent design and functionality allow them to detect intricate, non-linear interactions among multiple input variables. This makes them adept at managing complex relationships between independent and dependent variables.

## IV.2.2. Neuron model

### IV.2.2.1. Behavior



**Figure (IV.1).** Representation of a mathematical neuron.

By analogy with biology, an artificial neuron (Figure IV.1) receives information from the inputs  $x_i$  ( $i = 1, 2, \dots, m$ ) through connections, each of which is assigned a weight  $w$  to weigh the received information, also called synaptic weight. It operates in two steps:

The first phase represents the preprocessing of the received data by calculating the potential  $v_j$  of neuron  $j$  using the following function:

$$v_j = b_j + \sum_{i=1}^m w_{ij} \cdot x_i \quad (IV.1)$$

Where  $w_{ij}$  denotes the weight of the connection linking neuron  $j$  to input  $i$ , and  $b_j$  is a constant term called bias, which can be considered as the weight of an input  $x_0$  equal to 1. Thus, equation (IV.2) can be written more simply as:

$$v_j = \sum_{i=0}^m w_{ij} \cdot x_i \quad (IV.2)$$

The neurons used are linear neurons that perform a weighted sum of the inputs. However, there are others in the literature (distance neuron, polynomial neuron, kernel-type neuron, etc.). In the second phase, a transfer function  $f$ , also called an activation function, calculates the value of the internal state  $y_j$  of neuron  $j$  from the value of the potential  $v_j$ . This value will represent the output of the neuron:

$$y_j = f(v_j) = f\left(\sum_{i=0}^m w_{ij} \cdot x_i\right) \quad (IV.3)$$

### IV.2.3 Transfer functions

There are a lot of transfer functions the most used are: **The hard-limit transfer function**, which returns a 0 or a 1, is shown figure (IV.2). **The linear function** is a neural

transfer function. Transfer functions calculate a layer's output from its net input. The equation (IV.4) indicates the linear transfer function [34].

$$f(x) = x \quad (IV.4)$$

The equation (IV.2) describes the log-sigmoid transfer function.

$$f(x) = \frac{1}{1+e^{-x}} \quad (IV.5)$$

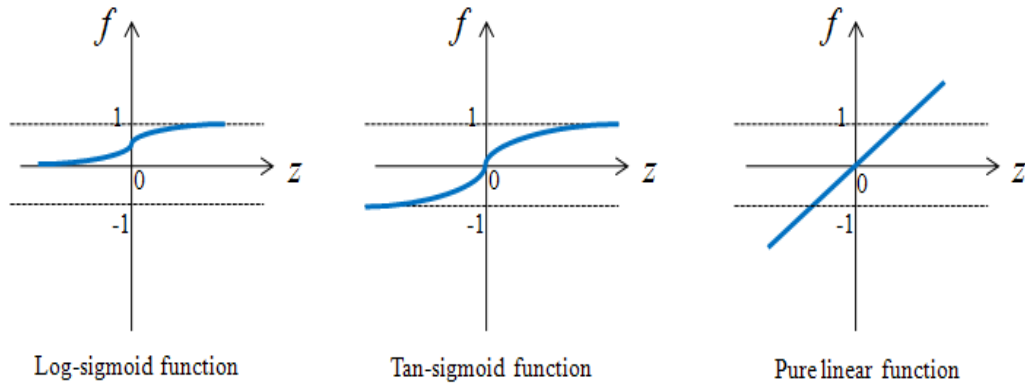


Figure (IV.2). The Most Transfer Functions Used.

## IV.2.4 Network architectures

### IV.2.4.1. Unidirectional Networks

These are feedforward networks without feedback loops. The output signal is obtained directly after the application of the input signal. If not, all neurons are output organs, they are referred to as hidden neurons [35-36].

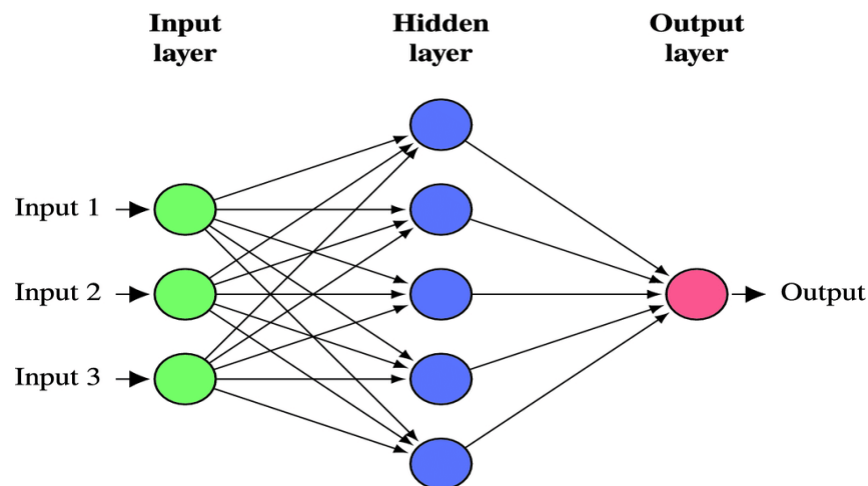


Figure (IV.3). Feedforward network

### IV.2.4.2. Feedback Networks

These are neural networks with feedback loops (feedback network or recurrent network) [37].

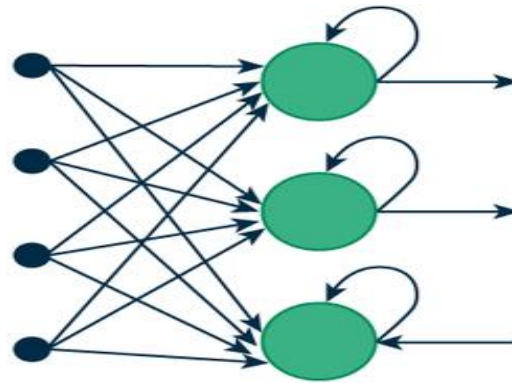


Figure (IV.4). Recurrent network.

### IV.2.5 Neural Network Design Steps

The good Neural Network results obtained by the right training. The standard steps for designing neural networks are given bellow [37].

- Data collection.
- Selection of network structure.
- Training the network.
- Testing the network.

### IV.2.6 The Mean Squared Error MSE

The validation of the network justified by the convergence of the output to the target *i.e.*, a small MSE [06].

$$MSE = \frac{1}{N} \sum_{k=1}^N (t_i - \alpha_i)^2 \quad (IV.6)$$

Where:  $N$ : the number of outputs and  $t$ : target.

The reduction of MSE obtained by adjusting the weights. So, the needs of back-propagation algorithm.

### IV.2.7 The back-propagation algorithm

The Back-propagation algorithm is an iterative method where the network evolves from an initial unlearned state to a fully learned state. The Gradient Descent (GD) is the first one developed by Rumelhart (1986). However, it's impractical for example, in the case of a lot of samples it was observed that training with the Stochastic Gradient Descent (SGD) is more generalized than with GD [38].

The learning phase of the multi-layer network consists of adapting the weights of the connections based on the prediction errors found. It can be distinguished two steps, the first one, The calculation of the derivatives error function MSE (W) with respect to the weights.

In the second step, the derivatives are then utilized to establish the adjustments to be made to the weights. After the two steps can be seen the effect of each weight over the prediction error and which weight has a big influence in reducing the error [39].

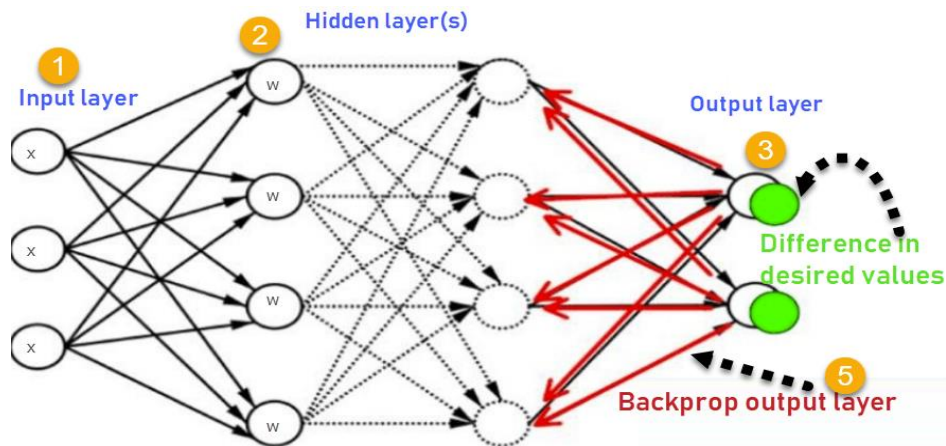


Figure (IV.5). The back-propagation algorithm.

### IV.3. The MPPT based on Neural Network

The Neural Network is used to make the system works in MPP. The proposed method is based on sensing the most important factors which influencing in the power (irradiance, temperature) and controlling the system by varying the duty cycle. The figure (IV.6) shows the architecture of the proposed method.

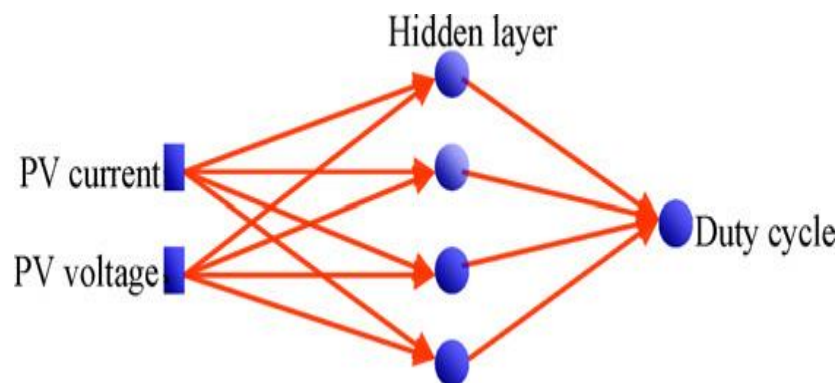


Figure (IV.6). The Proposed ANN Algorithm.

In this work, the proposed (ANN) aims to predict the maximum power point (MPP) of PV array. The four steps for designing ANN can be summarized by:

- Selection of ANN architecture
- Data collection
- Training the ANN
- Testing the ANN

We have used a Multi-Layer Perceptron (MLP) network, contains three layers as shown in fig (IV.6):

- The first layer: where the inputs to the network are the PV current ( $I_{pv}$ ) and voltage ( $V_{pv}$ ) of PV system recorded under different temperature and irradiance
- The second layer: is the hidden layer, contains 10 hidden neurons which receive data from the input layer and send them to the output layer. Its activation functions are the sigmoid functions (Tansig)
- The third layer: is the output layer, contains one neuron duty cycle (D) whose activation function is linear function (Purelin).

#### IV.3.1. Data Collection

The first step in designing an ANN is to collect data (inputs, outputs). Getting more data enhance the performance of NN. In our case lots of current and voltage and their corresponding duty cycle ratios are taken.

The samples are obtained by the collection of data from simulations of the Perturb and Observe (P&O) MPPT method conducted under a diverse range of climatic scenarios. With supervised learning, was used tagged data, i.e, a collection of data that already has been known, to determine a learning algorithm.

#### IV.3.2. Selection of Network Structure

The structure and the configuration of the network influence on the results. The choice of NN structure means setting all the parameters of network, i.e, the type of network, the number of layers, the number of neurons in each layer and the activation function. In addition, Log-Sigmoid Transfer Function is usually used in back-propagation network because it's differentiable. Until now, there are no guidelines method for deciding the number of layers and neurons needed, it is about varying them until reach the best results [41].

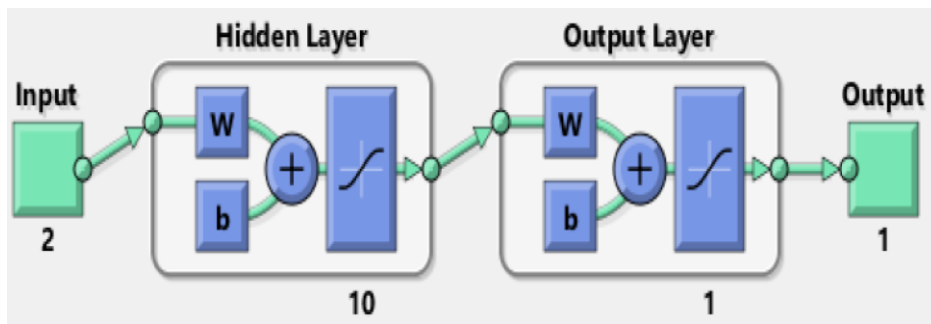


Figure (IV.7): Structural Model of the Neural Network in Matlab

### IV.3.3. Training and Testing the Network

After setting the NN design, the collecting data are provided for training. The training algorithms using the training function to adjust and update the weights.

The *nnTool/Toolbox* can be used to design, train, validate and test a neural network in Matlab, the data set are divided into three parts 70% for training, 15% for validation, and 15% for testing. The neural network is trained with Levenberg-Marquardt backpropagation algorithm, which is a very fast and accurate technique for minimizing the mean square error (MSE) as shown in figure (IV.8). This algorithm provides better results than others. As shown in figure (IV.9), the regression analysis is performed to measure the correlation between target and output.

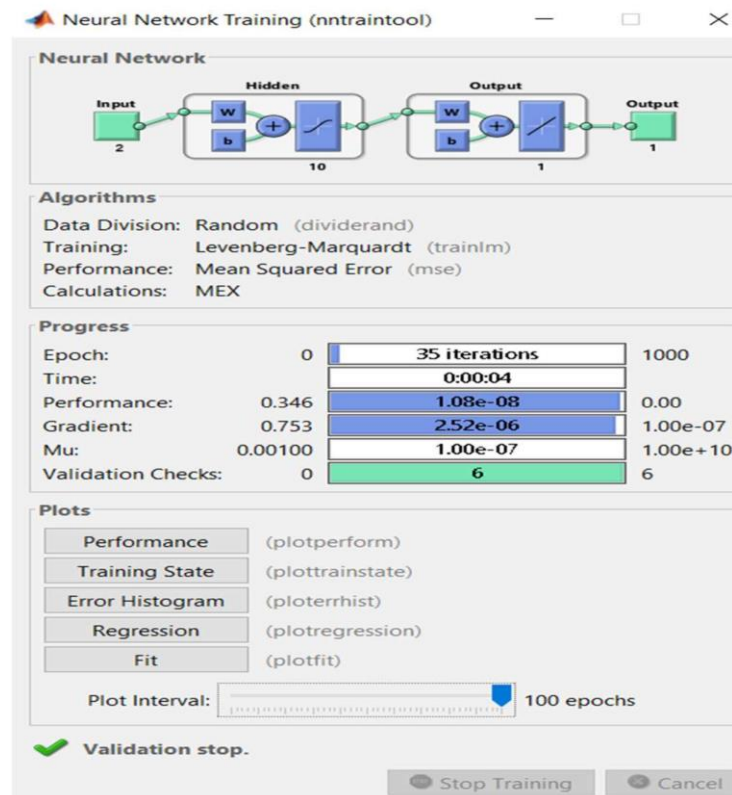


Figure (IV.8): Training neural network

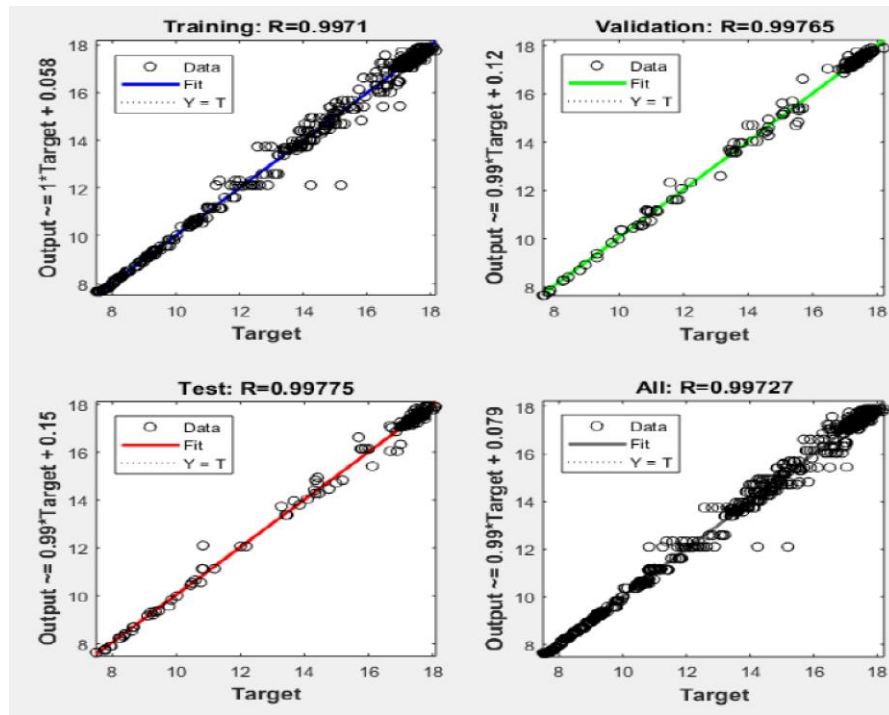


Figure (IV.9). Regression

### IV.4. Simulation of ANN-MPPT

❖ **Fixed profile:** The system is simulated under standard conditions, with constant irradiance ( $E=1000$  W/m<sup>2</sup>) and temperature ( $T=25^{\circ}\text{C}$ ). This helps establish a baseline performance for the ANN-MPPT algorithm.

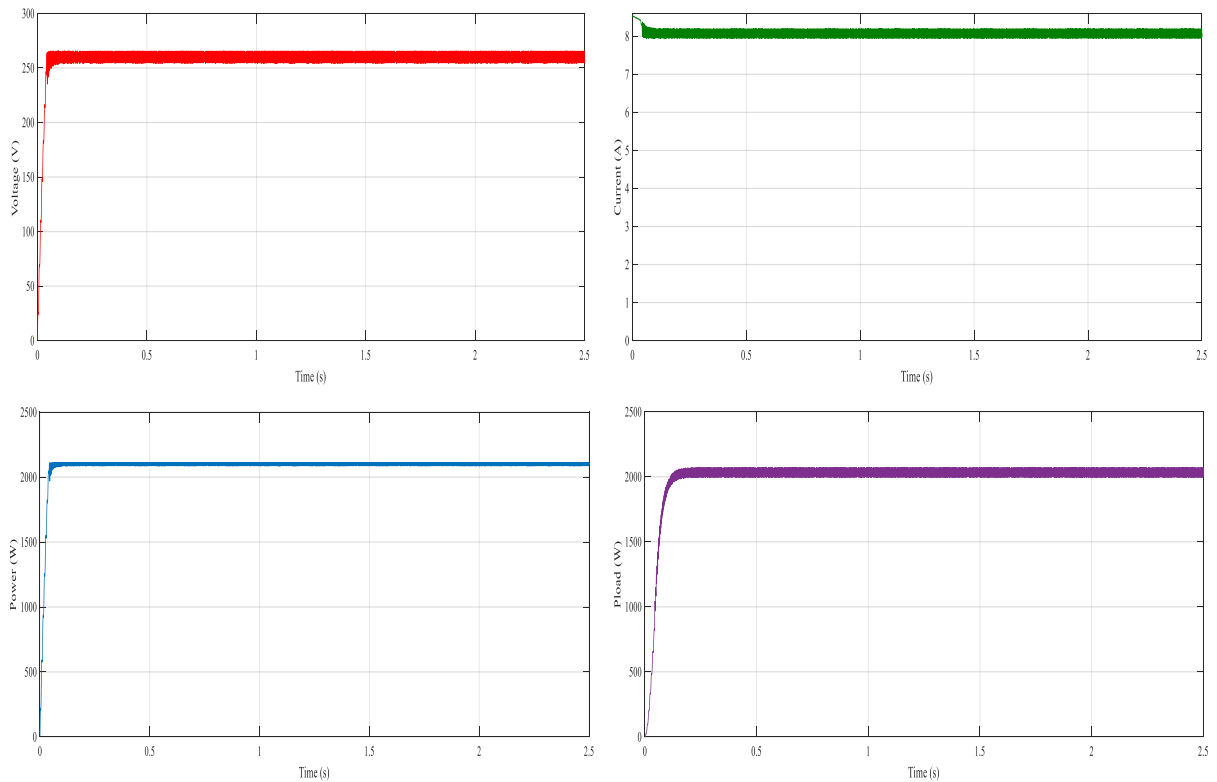


Figure (IV.10). Simulation results of the PV at ( $T=25^{\circ}\text{C}$ ,  $E=1000\text{W/m}^2$ ).

The results from figure (IV.10) indicate that the ANN-MPPT algorithm performs well under these fixed conditions. It achieves a fast response time of 0.12 seconds and high accuracy (99.93%) in finding the Maximum Power Point (MPP) from the solar panel array. This suggests the algorithm effectively controls the PV system to extract maximum power under constant irradiance and temperature.

❖ Variable profile: variable irradiation and constant temperature

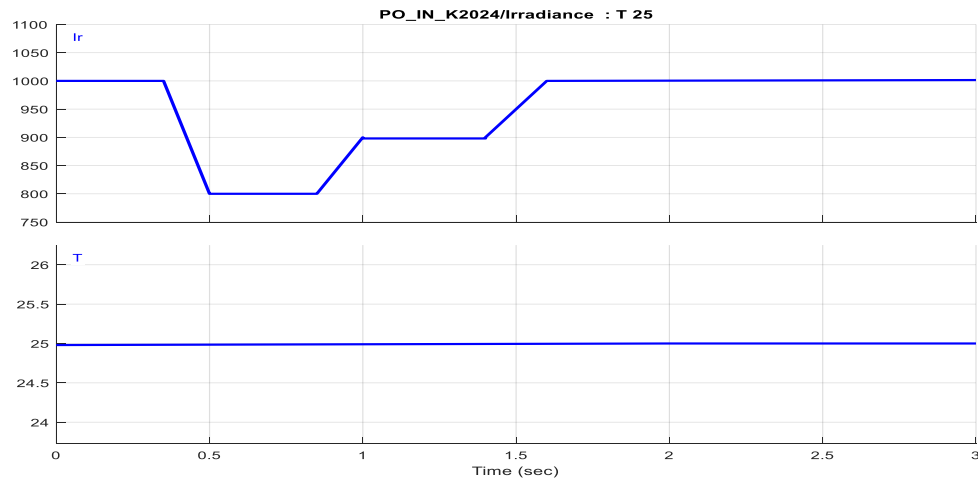


Figure (IV.11). Signal Builder for variable irradiation

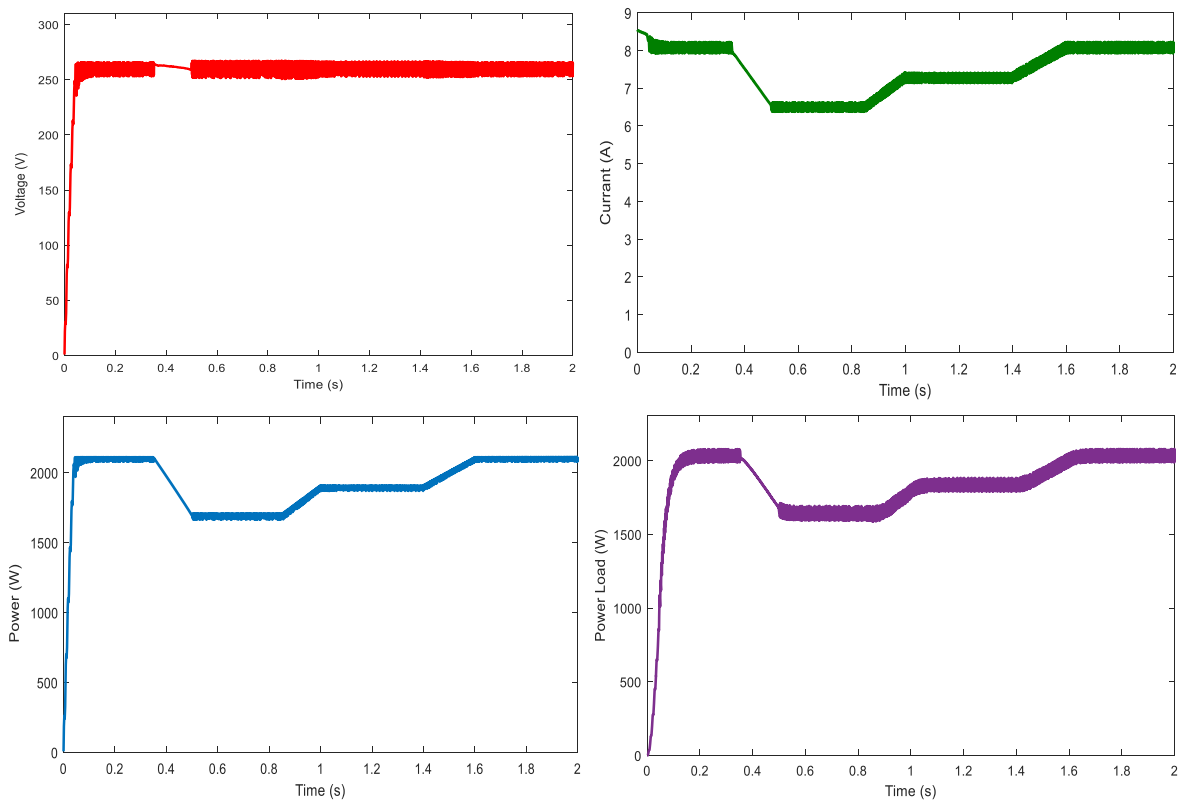


Figure (IV.12). Simulation Results of the PV

3. Variable profile: Variable temperature and constant irradiance

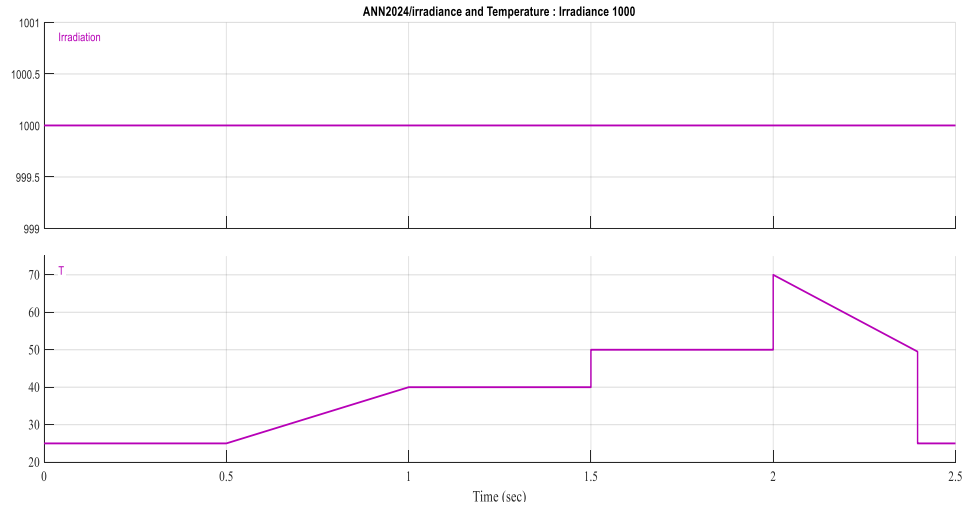


Figure (IV.13). Signal Builder for variable temperature.

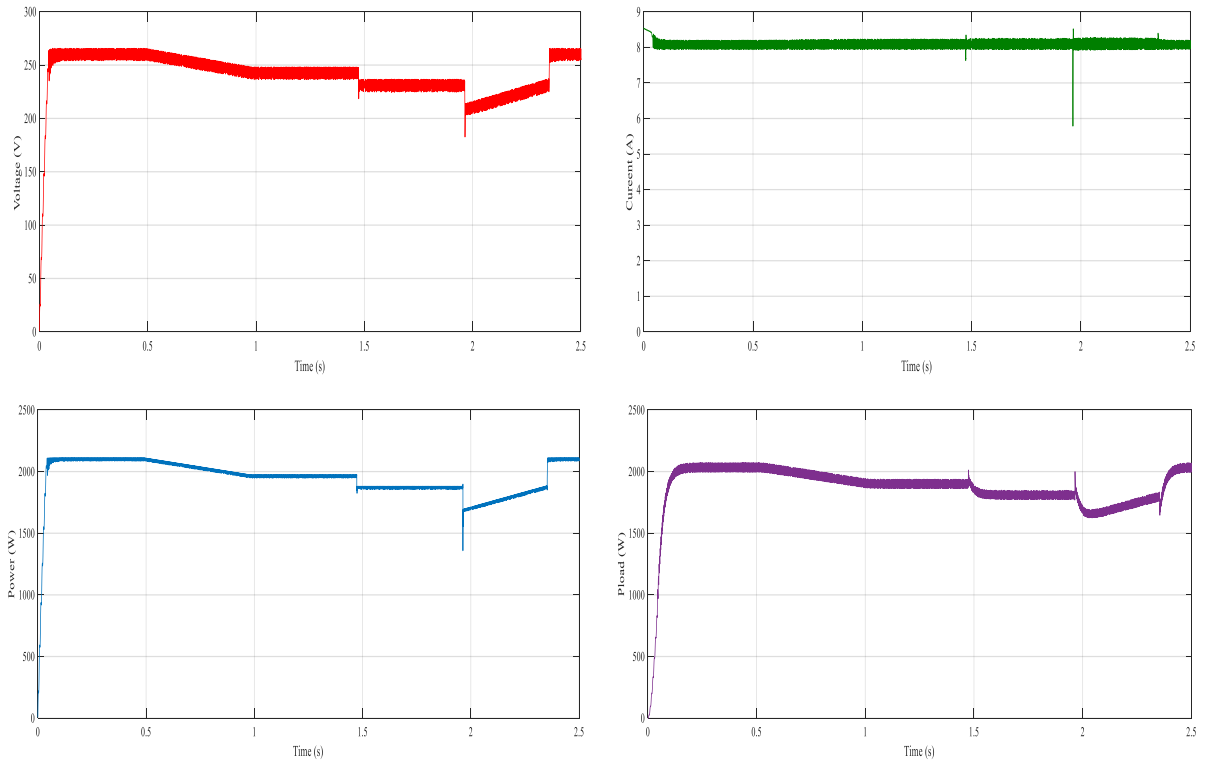


Figure (IV.14). Simulation results of the PV for variable temperatures ( $E=1000W/m^2$ ).

IV.5. Comparison Methods (P&O, INC, FLC and ANN)

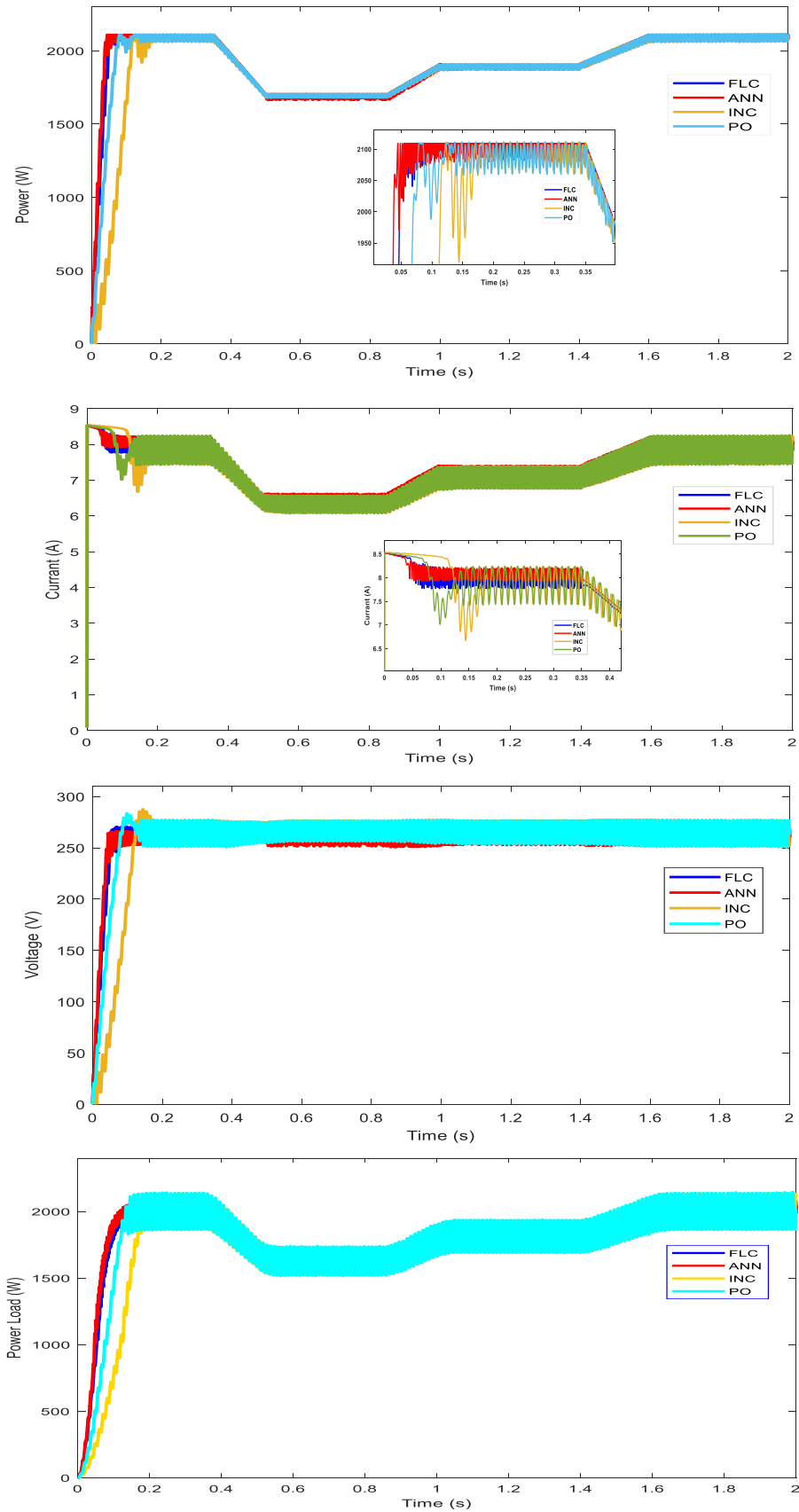


Figure (IV.15). Comparison methods for the different condition.

The test compares four MPPT algorithms (ANN, FLC, INC, P&O) by plotting their output power, voltage, current, and power load under different irradiance levels at a constant temperature, Figure (IV.15).

❖ **Algorithm Performance:**

- Neural Network (NN): ANN shines with its quick response (fast MPP reach) and high efficiency. It exhibits minimal power fluctuations, showing less oscillation around the MPP compared to other algorithms.
- Fuzzy Logic Control (FLC): FLC offers a good balance, achieving a relatively fast response (better than P&O and INC) and the highest tracking efficiency among the conventional methods discussed.
- Perturb and Observe (P&O): This widely used method exhibits some instability, oscillating around the MPP as irradiance changes, leading to power fluctuations.
- Incremental Conductance (INC): Similar to P&O, INC might show oscillation around the MPP under varying irradiance. It also takes longer to reach the MPP compared to NN and FLC.

## IV.6. Conclusion

In conclusion, this chapter delved into implementing Maximum Power Point Tracking (MPPT) techniques using Artificial Neural Networks (ANNs) within the *MATLAB* environment. We explored the intricate steps of data collection, preprocessing, network configuration, training, and performance evaluation, showcasing how an ANN can be trained for MPPT optimization.

Furthermore, the chapter compared the ANN-based MPPT approach under variable conditions (irradiance and temperature). This comparison revealed the advantages, such as potentially, and limitations of the ANN method, paving the way for further analysis and refinement, like exploring ANN performance in more complex scenarios or optimizing its architecture for even better MPPT results.

# **General Conclusion**

# General Conclusion

The widespread adoption of photovoltaic (PV) energy hinges on achieving the highest possible efficiency, stability, and reliability. This research investigates these crucial factors by exploring various Maximum Power Point Tracking (MPPT) techniques. The primary objective is to maximize the power output of a PV array under varying atmospheric conditions, particularly during rapid changes in weather patterns. Four prominent MPPT techniques are evaluated: Perturb and Observe (P&O), Fuzzy Logic Control (FLC), and Artificial Neural Networks (ANNs). The research aims to not only enhance the efficiency of PV power conversion but also improve the overall stability and reliability of the system. The following is an overview of the scope, main contributions and conclusions of the study:

Four common types of MPPT controllers, including the P&O, FLC, INC and ANN methods for PV electrical generation, have been developed based on simple optimization strategies to enhance a PV system further under different atmospheric conditions. The main features of each method were discussed to facilitate MPPT designers' understanding and thus, be able to select a suitable technique for their application area of interest. Then, the proposed methods were developed to improve their performance, especially under a rapid change in climatic conditions.

The proposed ANN-based MPPT energy harvesting concept holds potential for solving problems on a large scale and can be incorporated into multilayer neural networks, making it highly versatile. Furthermore, the study revealed a perfect correlation between input and output data, exemplified by the consistency between generated power and load power after MPPT. This ANN-based MPPT energy harvesting model can find applications in standalone and grid-connected solar PV systems, as well as military equipment, telecommunications, and space satellites. The suggested ANN-based MPPT energy harvesting model exhibits applicability across various domains and can be integrated into numerous technologies. Additionally, the

model can be utilized for solar radiation and temperature prediction, energy estimation, energy management in smart homes and cities, and forecasting solar radiation and temperature.

As we conclude this thesis, we anticipate a brighter and more sustainable energy future, where photovoltaic systems, enhanced by ANNs, play a central role. Our journey has contributed to the evolving landscape of renewable energy technologies, and we look forward to continued advancements and real-world applications of our findings.

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## APPENDICES

### ❖ Algorithm program (P&O-MPPT) and the following:

```

function D = PO(Vpv, Ipv)
    Dmax=0.9;
    Dmin=0.2;
    Dinit=0.4;
    deltaD=0.005;
    persistent Dpre Ppre Vpre;
    %first run
    if isempty(Dpre)
        Dpre=Dinit;
        Vpre=0;
        Ppre=0;
    end
    Ppv=Vpv*Ipv;
    dp=Ppv-Ppre;
    dv=Vpv-Vpre;

    if dp~=0
        if (dp>0)
            if (dv<0)
                D=Dpre+deltaD;
            else
                D=Dpre-deltaD;
            end
        else
            if (dv<0)
                D=Dpre-deltaD;
            else
                D=Dpre+deltaD;
            end
        end
    else
        D=Dpre;
    end

    if D>=Dmax || D <= Dmin
        D=Dpre;
    end

    Ppre=Ppv;
    Vpre=Vpv;
    Dpre=D;
end

```

### ❖ Algorithm program (INC-MPPT) and the following:

```

function y = IN(u, i, uo, io, D)
    m=0.9;
    du=u-uo;
    di=i-io;
    d=0.0005;
    if du==0
        if di==0
            m=D;
        else
            if di>0
                m=D-d;
            else

```

```

        m=D+d;
    end
end
else
    if di/du== -(i/u)
        m=D;
    else
        if di/du> -(i/u)
            m=D-d;
        else
            m=D+d;
        end
    end
end
end
y = m;
end
    
```

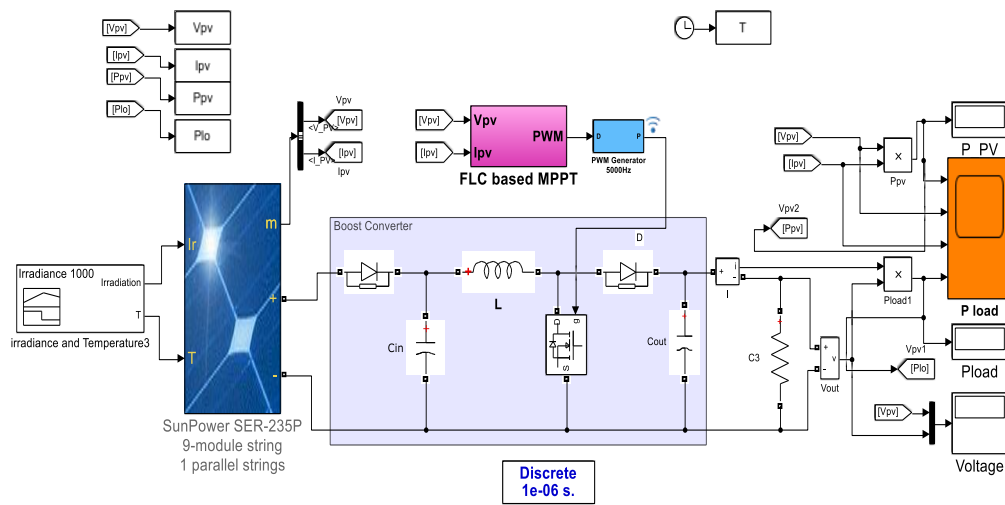


Figure (a). Block diagram of a photovoltaic system controlled by the MPPT (Fuzzy Logic).

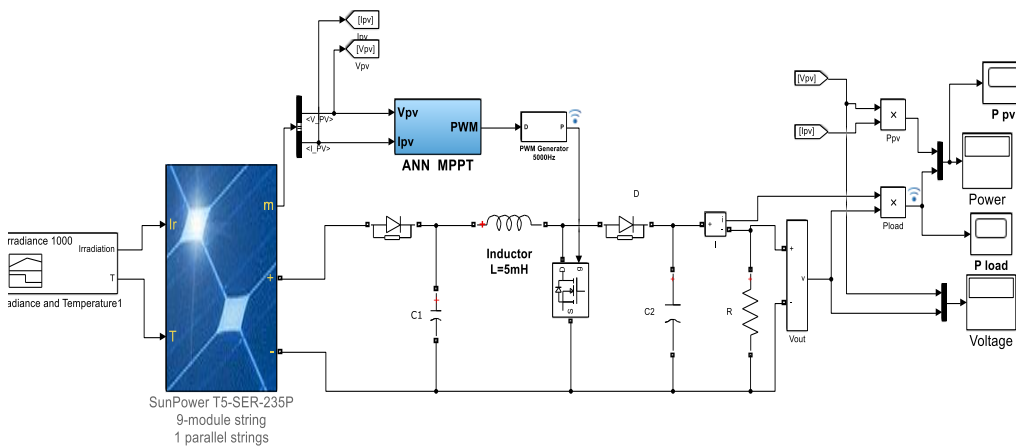


Figure (b). Block diagram of a photovoltaic system controlled by the MPPT (ANN).