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# Theme

# An Advanced Neural Network-Based MPPT Controller for Photovoltaic Systems

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بِسْمِ اللَّـهِ الرَّحْمَـٰنِ الرَّحِيمِ

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First and foremost, my deep thanks and gratitude to Almighty ALLAH, for His graces and blessings and for giving me strength and ability throughout the years of the Master to successfully complete my thesis.

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**ملخص** :

تتناول مذكرة الماستر هذه دمج الشبكات العصبية الاصطناعية (ANNs) في أنظمة الخلايا الضوئية لزيادة كفاءة تتبع أقصى نقطة للقدرة (MPPT). تعتبر أنظمة الخلايا الضوئية مصدرًا حاسمًا للطاقة النظيفة، وتعتمد بشكل كبير على تقنية MPPT الفعالة للحصول على أفضل أداء ممكن. الشبكات العصبية الاصطناعية، مستوحاة من الدماغ البشري، تظهر قدرات تكيفية رائعة، مما يجعلها مرشحًا مثاليًا لتحسين كفاءة أنظمة الخلايا الضوئية. أهداف البحث تشمل استكشاف تآزر الشبكات العصبية الاصطناعية مع أنظمة الخلايا الضوئية، وتحليل العوامل البيئية التي تؤثر على تقنية MPPT، وتطوير حلاً عمليًا قائمًا على الشبكات العصبية الاصطناعية لتحسين تقنية MPPT، وتقييم التأثيرات في العالم الحقيقي. يسلط البحث الضوء على إمكانية استغلال الشبكات العصبية الاصطناعية في رفع كفاءة استخدام الطاقة الشمسية ويسهم في تطوير الطاقة المتجددة.

**كلمات مفتاحية:** أنظمة الخلايا الضوئية، الشبكات العصبية الاصطناعية (ANNs)، تتبع أقصى نقطة للقدرة (MPPT)، الطاقة الشمسية، الطاقة المتجددة، العوامل البيئية، البحث والتحسين، الاستدامة، كفاءة الطاقة، محاكاة MATLAB

**Abstract**:

This master's thesis delves into the integration of Artificial Neural Networks (ANNs) into photovoltaic systems to enhance Maximum Power Point Tracking (MPPT) efficiency. Photovoltaic systems are a crucial source of clean energy, reliant on effective MPPT for optimal performance. ANNs, inspired by the human brain, exhibit remarkable adaptability, making them an ideal candidate for improving photovoltaic systems' efficiency. The research objectives encompass investigating ANNs' synergy with photovoltaic systems, analyzing environmental factors affecting MPPT, developing practical ANN-based solutions for MPPT optimization, and assessing real-world impacts. The study illuminates the potential of ANNs in elevating solar energy utilization and contributes to renewable energy advancements.

**Keywords:** Photovoltaic systems, Artificial Neural Networks (ANNs), Maximum Power Point Tracking (MPPT), Solar energy, Renewable energy, Environmental factors, Optimization, Sustainability, Energy efficiency, MATLAB simulation.

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# List of Acronym

| | |
|---|---|
| MPPT | Maximum Power Point Tracking |
| ANNs | Artificial Neural Networks |
| MATLAB | Matrix Laboratory |
| MSE | Mean Square Error |
| P&O | Perturb and Observe |
| Ts | Sampling Time |
| E | Insolation |
| V | Voltage |
| I | Current |

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# General Introduction

# General Introduction

The evolution of renewable energy technologies has ushered in a new era of sustainable power generation. Among these technologies, photovoltaic systems have emerged as a prominent source of clean energy, harnessing the abundant and inexhaustible power of sunlight. The efficacy of photovoltaic systems, however, hinges on their ability to maximize energy capture, especially in the face of varying environmental conditions. This imperative optimization task is achieved through the crucial component of Maximum Power Point Tracking (MPPT).

This master's thesis embarks on a comprehensive exploration of enhancing photovoltaic systems with the integration of Artificial Neural Networks (ANNs). ANNs, inspired by the functioning of the human brain, have demonstrated remarkable adaptability and learning capabilities, making them a compelling candidate for optimizing the performance of photovoltaic cells, particularly in the context of MPPT.

The research objectives of this study are to investigate the integration of Artificial Neural Networks (ANNs) into photovoltaic systems, focusing on enhancing Maximum Power Point Tracking (MPPT) efficiency. Specifically, the study aims to explore the synergy between ANNs and photovoltaic systems, analyze the impact of environmental factors on MPPT performance, develop practical ANN-based solutions for MPPT optimization, and assess the real-world impact of these enhancements. Through these objectives, this research seeks to advance our understanding of how ANNs can improve the utilization of solar energy.

The structure of this thesis can be summarized as follows:

Chapter I: Illuminating the Photovoltaic System

In this opening chapter, we embark on a journey through the fundamental concepts that underpin photovoltaic systems. We will delve into the intricate processes of solar energy conversion, tracing the historical development of these systems and laying the groundwork for our exploration. Moreover, we will contextualize solar energy within the broader spectrum of renewable resources, highlighting its inexhaustible nature and versatility in various environmental conditions.

Chapter II: Navigating the Path to Maximum Power Point Tracking (MPPT)

As our expedition continues, Chapter II will lead us into the realm of maximizing power point tracking (MPPT) strategies within photovoltaic systems. We will elucidate the operational principles governing MPPT regulators and explore their pivotal role in optimizing photovoltaic cell performance. Additionally, we will delve into the significant impact of environmental variables such as insolation, temperature, and shading on the effectiveness of MPPT regulators.

Chapter III: Unveiling the Potential of Artificial Neural Networks (ANNs)

Chapter III marks a pivotal juncture in our exploration as we venture into the world of Artificial Neural Networks (ANNs). Inspired by the intricate workings of the human brain, ANNs have revolutionized various domains, including photovoltaic systems. We will gain a comprehensive understanding of ANNs, their diverse learning methods, and their wide-ranging applications.

Specifically, we will focus on the symbiotic relationship between ANNs and photovoltaic systems, with a keen emphasis on their role in optimizing MPPT. ANNs empower photovoltaic systems to dynamically adapt to changing environmental conditions, thereby maximizing energy capture.

Chapter IV: Bridging Theory and Practice – Implementing MPPT with ANNs in MATLAB

In this practical chapter, we bridge the theoretical foundations with real-world application. Our journey will lead us to the practical implementation of ANNs to enhance the performance of photovoltaic systems, with MATLAB as our chosen tool. Through a series of simulations and experiments, we will provide tangible evidence of the real-world impact of ANNs on photovoltaic systems, showcasing their ability to fine-tune power output in response to varying conditions.

Conclusion: Illuminating the Path Forward

In conclusion, this master's thesis embarks on a transformative journey aimed at unlocking the full potential of photovoltaic systems through the integration of Artificial Neural Networks. By harnessing the capabilities of ANNs, our objective is to elevate the efficiency and sustainability of solar energy generation. As we navigate through each chapter, we will unravel the intricacies of these systems, explore their practical applications, and ultimately contribute to the advancement of renewable energy technologies. Our voyage is one of discovery, innovation, and progress, as we illuminate the path forward for a brighter and more sustainable energy future..

# Chapter I:

## The Photovoltaic System

### I.1 Introduction

A portion of solar radiation is converted into electrical energy through the photovoltaic cell, which produces photovoltaic solar energy. This new source of renewable energy has proven its effectiveness due to its high flexibility and ability to operate in challenging conditions. In this chapter, we will delve into the general concepts of solar energy, the equivalent model of a photovoltaic cell, and the details of a photovoltaic generator.

## I.2. Historical Background

The development of photovoltaic systems is the result of continuous work over many years and contributions from various scientists throughout history. We will highlight key milestones in this development:

**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%, just as the emerging space industry was seeking new solutions to power its satellites.

**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.

**2000:** The EEG Renewable Energy Sources Act (EEG) came into effect on April 1, 2000, and was modified in 2004 and 2009. It resulted from the transposition of the European directive on the promotion of renewable energies in the electricity sector.

**2005:** In December 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, 79576 Weil am Rhein. This discovery, later referred to as the "photoelectric effect," had a significant impact on the development of photovoltaic panels.

## I.3. The Photovoltaic Effect

The photovoltaic effect is a process by which light is converted into electricity. It was first experimented with in 1839 by Henri Becquerel when he submerged a platinum (Pt) foil coated with a thin layer of silver chloride in an electrolytic solution and then exposed the foil to light while it was connected to a counter electrode [2].

In PV technology, electrical power in direct current (DC), measured in watts (W) or kilowatts (kW), is generated from semiconductor materials when they receive photons in a lighting process [3].

Functionally, individual PV elements, primarily known as solar cells, include a p-n junction within a semiconductor material where light absorption has occurred. Solar cells never need recharging to produce electricity again, as is the case with a battery. Therefore, the production of electrical energy continues as long as light is projected onto a solar cell. Once the illumination is interrupted, electricity production also ceases [2, 3].

## I.4. Operation of a Photovoltaic Cell

For a photovoltaic cell, the process is as follows:

The penetration of "grains" of light (photons) into the silicon displaces some of the electrons from the material. A semiconductor material allows electrons to move in only one direction, and the electrons struck by light must pass outside a circuit to return to their original state, generating current [5].

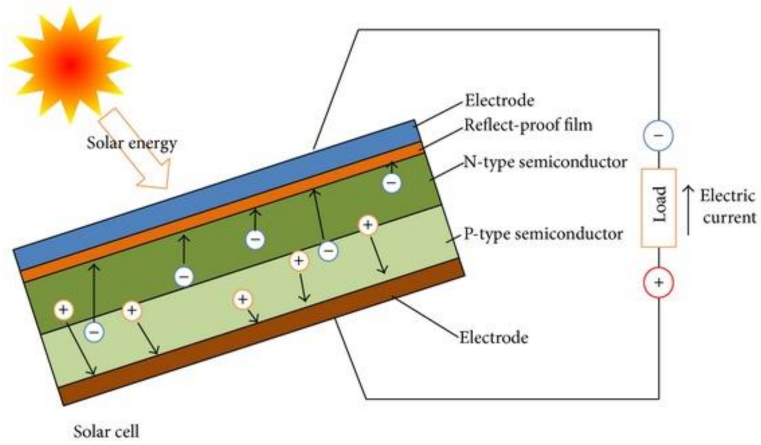


Figure I.1: Operation of a Photovoltaic Cell [6]

### I.4.1. Interaction of Light with Matter

Photons generated from solar radiation carry energy estimated by the following relationship: [7]
Where E is the amount of energy, λ is the wavelength, h is the Planck constant, and c is the speed of light. Silicon absorbs incident photons based on their wavelength. Therefore, shorter-wavelength photons, which are more energetic (ultraviolet), are absorbed within the first micrometer of the cell, while longer-wavelength photons (infrared) can reach the rear face and be reflected. The limited bandwidth Eg is an important factor as it determines the absorption threshold. The photon interacts with the electron, which can provide a significant amount of energy.

### I.4.2. Transfer of Energy from Photons to Electrons

Electron-hole pairs, formed from the energy of incident photons, are commonly referred to as photogenerated carriers. The minority carriers, carrying electrons in a doped substance and holes in a doped substance, diffuse under the influence of concentration gradients toward the interface. They are then propelled by the electric field and reach the region where they are the majority to participate in the electric current flowing through photosensitive devices [7].

### I.4.3. Collection of Electric Charges

The material receiving light must be a semiconductor so that each photon can transfer the amount of energy it carries, an intermediate state between an insulator, where electrons cannot move, and a conductor, where electrons are completely free to move.
When light enters a semiconductor, its photons provide the energy that allows electrons to move, thus generating an electric force within the material [8].

## I.5. General Principle of a Photovoltaic Cell

The operation of a photovoltaic cell is based on the properties of semiconductors, which, when struck by photons, set in motion a flow of electrons. Photons are elementary particles that carry solar energy at a speed of 300,000 km/s and were referred to by Albert Einstein in the 1920s as "particles of light." When they strike a semiconductor element like silicon, they dislodge electrons from its atoms. These electrons move in a disorderly fashion, seeking other "holes" to reposition themselves.

However, for an electric current to flow, these electron movements must all go in the same direction. To facilitate this, two types of silicon are combined. The side exposed to the sun is "doped" with phosphorus atoms that contain more electrons than silicon, while the other side is doped with boron atoms containing fewer electrons. This double-sided structure becomes a sort of stack: the side heavily laden with electrons becomes the negative terminal (N), and the side with fewer electrons becomes the positive terminal (P). A built-in electric field is created between them.

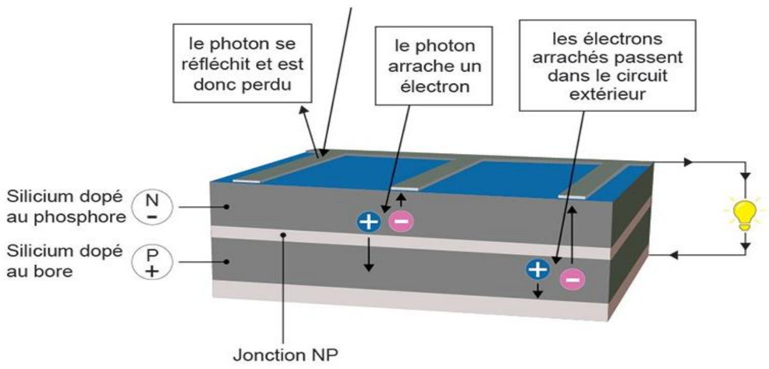


Figure I.2: Diagram of a PV Cell [4]

When photons excite the electrons, they migrate to the N-zone thanks to the electric field, while the "holes" move toward the P-zone. They are collected by electrical contacts at the ends of the zones, entering the external circuit as electrical energy. A direct current is generated. An anti-reflective layer prevents too many photons from being lost by being reflected from the surface [4].

## I.6. Photovoltaic Solar Energy

The sun is an inexhaustible source of energy, with the solar radiation reaching the Earth's surface representing approximately 8,400 times the annual energy consumption. This corresponds to an instantaneous peak power of 1 kW per square meter spread across the entire spectrum, from ultraviolet to infrared. Photovoltaic solar energy involves producing electricity directly from light using solar panels. The energy comes from photons (components of light) that collide and release electrons, creating an electric current. This direct current can be converted from a small power measured in peak watts (Wp) to alternating current using an inverter [7].

The electricity produced is available in the form of direct current, stored in batteries (decentralized electrical energy), or injected into the grid.

The photovoltaic solar generator is composed of photovoltaic modules made up of interconnected photovoltaic cells [6].

## I.7. Components of a PV Module

In the production of the PV module, encapsulation aims to assemble the cells in series or in parallel to allow them to be used at practical voltages and currents while ensuring their electrical insulation and protection against external aggressions. This protection should enable a useful life of the PV modules exceeding 20 years.

Encapsulation involves placing a unit consisting of cells and encapsulation material (EVA) between two glass panels (double glazing process) or between a sheet of glass and a unit consisting of thin layers of polymer (tedlar, mylar) and aluminum (single glazing process).

The photovoltaic cells are encapsulated between two layers of manufactured thermoplastics [9].

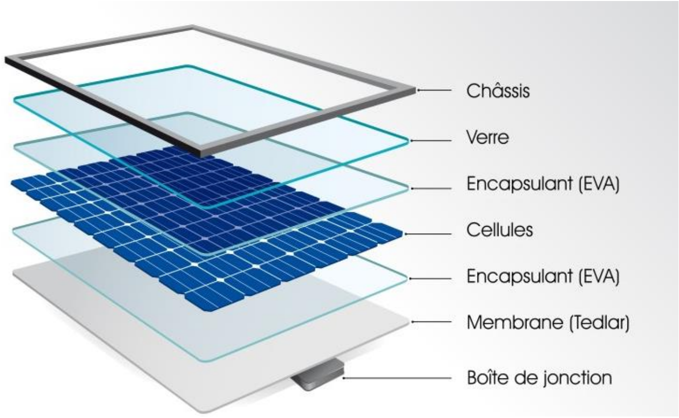


Figure I.3: The Different Layers Constituting a PV Module

## I.8. PV Cell Models

The implementation of photovoltaic system modeling aims to generate fault indicators (symptoms) for our diagnostic system. The goal of the diagnostic system is to detect and identify faults on the DC side of the photovoltaic system, and we have chosen to focus the photovoltaic system analysis on the DC side of the photovoltaic generator. [7]

### I.8.1. Single-Diode Model

Also known as the Rp-Model, this model takes into account not only voltage losses expressed by the series resistance Rs but also current leaks expressed by a parallel resistance Rp [10,11,12,13].

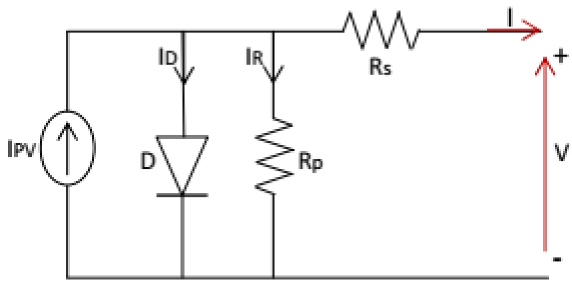


Figure I-4 Equivalent Circuit of a PV Cell – 1-D Model

This is the model on which manufacturers base the technical specifications of their solar cells (data sheet). It is also considered satisfactory and even a reference for manufacturers to catalog solar modules. The equation for the current delivered by the photovoltaic cell is described as follows:

$$I = Ipv - Io + Is\left[exp\left\{\frac{(V)}{aVt}\right\}\right] - \left(\frac{V+IRsy}{Rp}\right) \qquad (I.1)$$

Rp: Resistance modeling leakage currents of the junction

### I.8.2. Model with Ohmic Losses µ (Rs-Model)

This model takes into account material resistivity and ohmic losses due to contact levels, providing a better representation of the electrical behavior of the cell compared to the ideal model [10,11]. These losses are represented by a series resistance Rs in the equivalent circuit shown below:

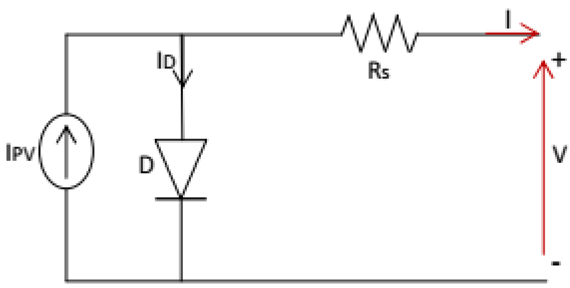


Figure I-5 Equivalent Circuit of a PV Cell – Rs-Model

After analyzing the circuit, the current-voltage equation is given as follows:

Avec : $I = I_{pv} - I_o + I_s \left[exp\left\{\frac{(V+IRs)}{aVt}\right\} - 1\right]$ (I.3)

Rs: Series resistance characterizing various contact and connection resistances.

### I.8.3. Ideal Model

The previous discussion leads us to the equivalent electrical model of the photovoltaic cell represented in Figure II-2, known as the ideal model. It is the simplest model to represent the solar cell, as it considers only the diffusion phenomenon. The simplified equivalent circuit of a solar cell consists of a diode and a current source connected in parallel [11].

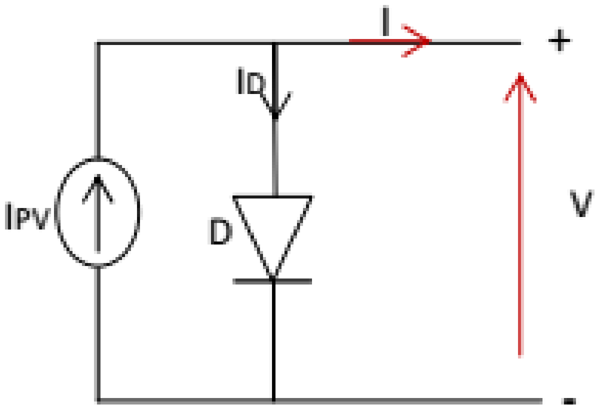


Figure I.6: Equivalent Circuit of a PV Cell – Ideal Model

The current-voltage (I-V) equation of the equivalent circuit is given as follows:

I = Ipv – ID

I: Current supplied by the cell [A]

Ipv: Photon current of the cell proportional to the irradiance (G)

Avec : $I = I_{pv} - I_o + I_s \left[exp\left\{\frac{(V)}{aVt}\right\} - 1\right]$ (I.2)

Io: Reverse saturation current of the diode.

Vt: Thermodynamic potential.

K: Boltzmann's constant (1.38 x 10^-23 Joules/Kelvin).

T: Cell temperature in Kelvin

q: Charge of an electron = 1.6 x 10^-19C

a: Ideality factor of the junction.

V: Voltage across the cell

### I.8.4. Empirical Model

This model describes the behavior of the PV cell. Its major advantage is the limited number of parameters that can be easily found in the data sheets of manufacturers.

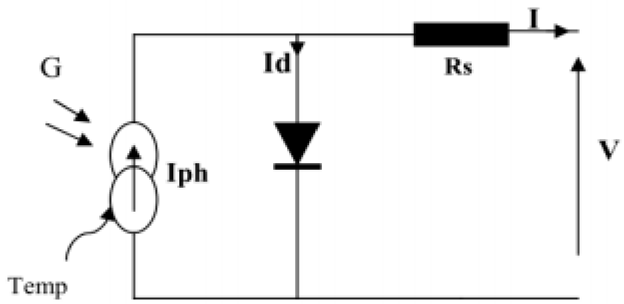


Figure I.7: Simple Equivalent Circuit of the PV Cell [7]

The relationship between the output current and the cell voltage is derived from

$$Iph = \Phi/\Phi ref\ Iph = \frac{\Phi}{\Phi ref}\left[\ Iph_{ref} + \mu Ics\ (T - Tref\ )\right] \quad (I.6)$$

$$Is = I_{sref}\ .\ \left(\frac{T}{Tref}\right)^{3}.\ \exp\left[\left(\frac{q.Eg}{Ak}\right).\left(\frac{1}{Tref}\right) - \left(\frac{1}{T}\right)\right] \quad (I.7)$$

Equation 2.1 assuming Rsh = ∞ [7]

### I.8.5. Two-Diode Model

The equivalent circuit in Figure I.7 represents the two-diode model of a PV cell; the solar cell under illumination is modeled as a photo-current source connected with two ideal diodes and two resistances: series (Rs) and shunt (Rp). Diode D1 reproduces the diffusion process, while D2 represents carrier recombination. Thus, the current passing through the first diode ID1 is the diffusion current, and the current passing through the second diode ID2 is the recombination current in the space charge region. These contribute to the saturation currents of a solar photovoltaic cell [14].

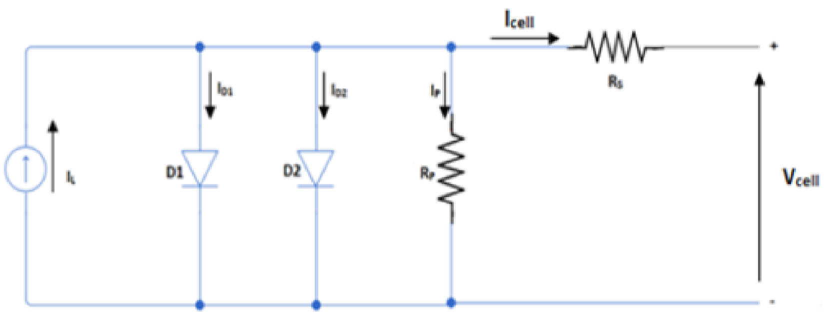


Figure I.8: Equivalent Circuit Diagram of the PV Cell with Two-Diode Model, Series Resistance, and Shunt Resistance.

The I-V characteristic equation contains two exponential terms. The output current of the PV generator is given by the following equation:

$$I_{cel} = I_L + I01\left[exp\left\{\frac{q(Vcel-Rs.I)}{a1.k.Tcel}\right\}-1\right]+I02\left[exp\left\{\frac{q(Vcej-Rs.I)}{a2.k.Tcel}\right\}-1\right]-\frac{Vcel+RsI}{Rp} \qquad (I.4)$$

Where

I01 and I02: Saturation currents of the first and second diodes, respectively.

Ns: Number of PV cells connected in series in the PV module

a1 and a2: Ideality factors of the diode representing diffusion and recombination current components, respectively.

For more diodes connected in different express series:

$$I_{Ns} = I_L + I01\left[exp\left\{\frac{q(Vcel-Rs.I)}{a1.Ns.k.Tcel}\right\}-1\right]+I02\left[exp\left\{\frac{q(Vcej-Rs.I)}{a2.Ns.k.Tcel}\right\}-1\right]-\frac{Vcel+RsI}{Rp} \qquad (I.5)$$

### I.8.6 Bishop Model

The Bishop model takes into consideration the avalanche effect of the cell by adding to the single-diode model a nonlinear multiplier M(V1) in series with the shunt resistance. This multiplier corresponds to the last term in equation (II-1), which relates the current (I) and voltage (V) of a PV cell [15].

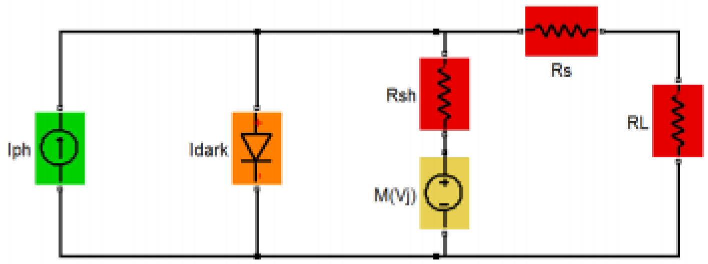


Figure I.9: Equivalent Diagram of a PV Cell - Bishop Model [7]

Combining multiple PV cells in series or parallel results in a PVG. When cells are connected in series, their voltages add up, increasing the total voltage of the generator. Conversely, if cells are connected in parallel, the amperage increases.

Most commercial PV panels consist of subarrays of cells connected in series. Each of these subarrays is itself made up of a group of PV cells connected in series. The number of cells per subarray is a result of an economic compromise between protection and losses in case of partial PVG failure.

Similar to individual cells, it's important to note that the electrical characteristic I(V) of a PVG is nonlinear and has a point of maximum power (MPP). This point also has associated current and voltage values called Iopt and Vopt, respectively. The operating point of a PVG depends on the load impedance it feeds. This load could be a resistive load or a direct current (DC) bus (e.g., connected to a battery). In the case of a battery, it dictates the operating point of the PVG during a direct connection.

Figure I.10 illustrates the schematic commonly used for a basic PVG. For all the tests conducted in this thesis, we had access to BP585 PV modules consisting of two sets of 18 PV cells each. Their traditional operating environment includes the connection of two bypass diodes and a reverse diode. The physical connections allow for operation with or without diodes, depending on the desired conditions [16].

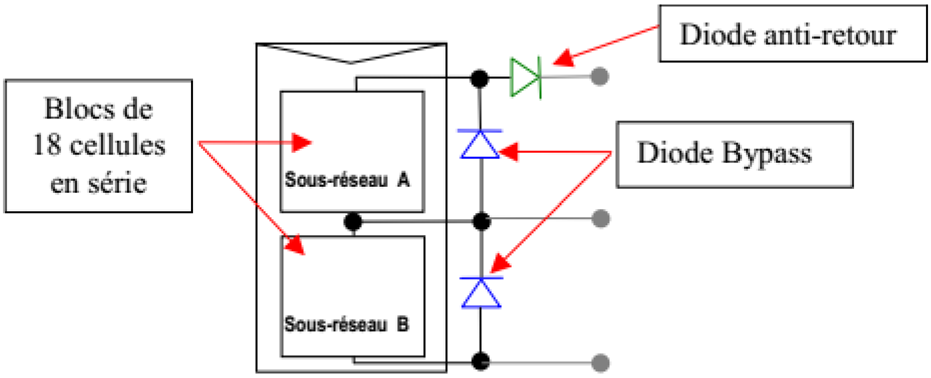


Figure I.10: Schematic of a Basic PVG with Bypass Diodes and Reverse Diode

## I.9. Conclusion

In conclusion, this first chapter provided a comprehensive overview of photovoltaic systems, tracing their historical development from the discovery of the photovoltaic effect in 1839 to the present day. We discussed the fundamental principles of photovoltaic energy conversion, including the interaction between light and matter, energy transfer from photons to electrons, and the collection of electric charges in semiconductor materials.

Furthermore, we explored the basic operation of a photovoltaic cell, emphasizing the generation of electric current through the movement of electrons in response to photon absorption. The chapter delved into the concept of the photovoltaic effect, highlighting its significance in harnessing solar energy.

The discussion also encompassed the broader context of solar energy, emphasizing the inexhaustible and environmentally friendly nature of solar radiation. Additionally, we touched upon the various models used to characterize photovoltaic cells, which play a crucial role in understanding their behavior and optimizing their performance.

Overall, Chapter I laid the foundation for the subsequent chapters, which will delve deeper into the specifics of maximum power point tracking (MPPT) and advanced neural network-based controllers for photovoltaic systems. Through this exploration, we aim to contribute to the advancement of efficient and intelligent photovoltaic energy conversion techniques

# Chapter II:

## Strategies for Maximizing Power Point Tracking (MPPT) in Photovoltaic Systems

## II.1. Introduction

In this chapter, we delve into the pursuit of the Maximum Power Point Tracker (MPPT), a pivotal component in solar energy systems. It plays a crucial role in harnessing energy generated by solar cells and regulating DC power output according to the system's voltage requirements. The MPPT operates as a DC/DC converter, modulating current flow in pulses, similar to PWM, but with the advantage of optimizing energy utilization from the solar cells by reducing voltage while increasing current [19].

## II.2. Pursuit of the Maximum Power Point Tracker (MPPT)

The solar charge regulator MPPT, a fundamental component of the solar system, plays a pivotal role in harnessing the energy generated by solar cells and regulating DC power in accordance with the approved system voltage. It functions as a DC/DC converter, modulating electric current in pulses similar to PWM. However, it possesses the advantage of optimally utilizing the energy produced by solar cells by reducing voltage while increasing current [19].

### II.2.1. Operating Principle of the MPPT Regulator

The fundamental principle of the MPPT regulator is to extract the maximum electrical energy from solar cells by operating them at their most efficient voltage, known as the Maximum Power Point (MPP). Subsequently, the regulator works to reduce the total panel voltage to match the charging voltage and obtain the maximum charging current for the battery. Additionally, it can efficiently power DC electrical loads [19].

### II.2.2. MPPT Regulator Efficiency

Several conditions enhance the effectiveness of the MPPT regulator compared to the PWM regulator:

**1.** Cold Weather: Solar panels perform optimally in colder temperatures, making MPPT more effective in extracting maximum energy from cells.

**2.** High Battery Discharge Depth: MPPT accelerates the battery charging process, especially when the battery voltage is low [19].

### **II.2.3.** Effects of Environmental Factors on the MPPT Regulator

The characteristics of the solar cell are significantly influenced by the following environmental factors:

**1.** Insolation

**2.** Temperature

**3.** Partial Shading Conditions

The impacts of these environmental factors are explained as follows.

**II.2.2.1.** Impact of Insolation

Changes in characteristics with varying insolation are illustrated in Fig I.17. The short-circuit current (Isc) of the solar cell is insolation-dependent and decreases proportionally with decreasing insolation. Figure 9 demonstrates that the maximum power point also varies with changing insolation [20].

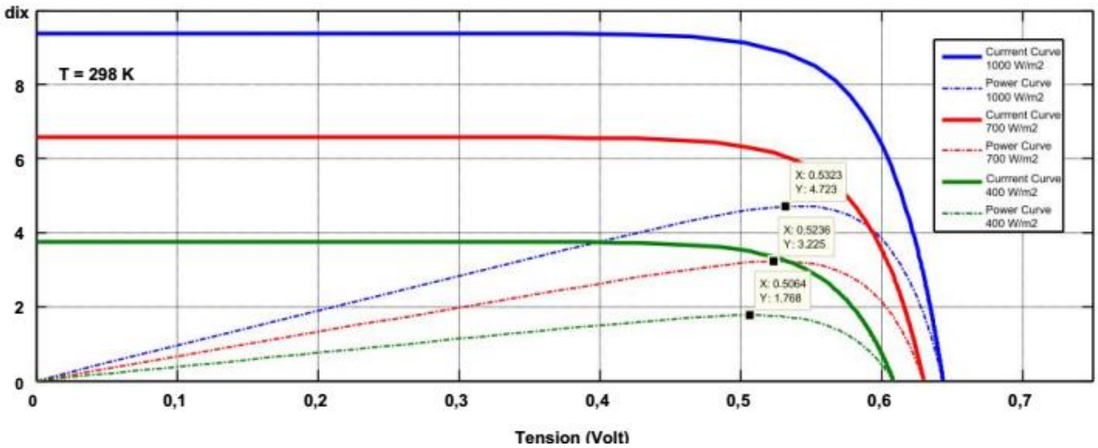


Fig II-1: Solar I-V and P-V Characteristics with Different Insolation Levels and Constant Temperature [20].

**II.2.2.2.** Impact of Temperature

Temperature is another significant factor that influences the characteristics of a solar cell. With increasing temperature, the open-circuit voltage increases proportionally, but the short-circuit current decreases logarithmically. Figure I.17 illustrates this characteristic of solar cell characteristics for various temperature values [20].

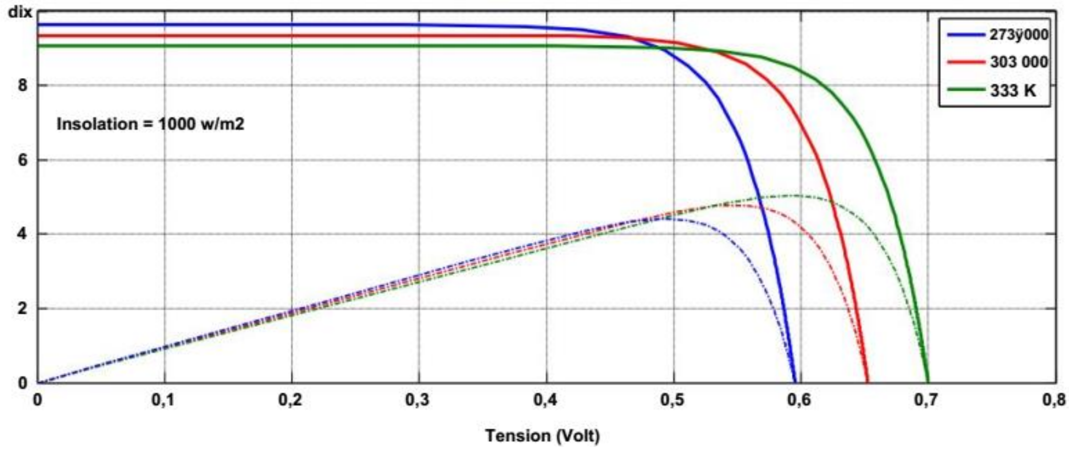


Figure II-2: Solar Cell Characteristics at Different Operating Temperatures with Constant Insolation [20].

**II.2.2.3.** Impact of Shading

In addition to temperature and insolation, partial shading also has a significant impact on the characteristics of solar cells. When multiple PV modules are connected, and one of them is partially shaded, the sunlight received by the two modules differs. This mismatch condition is explained by considering an example of two solar cells, Q6LMXP3-G3, connected in series with their terminal voltages V1 and V2, total power P, and total voltage V, as indicated in Fig. I.19. It demonstrates the shading condition with the bypass diode attenuation strategy. Fig. I.20 shows the characteristic of the solar PV for this shading condition.

As explained above, all these factors, which vary over time and depend on the environment, contribute significantly to changes in the operating point or maximum power point (MPP) throughout the day. The purpose of maximum power point tracking (MPPT) is to move this changing operating point to the point (Pmax) where the module delivers maximum power. The phenomenon of maximum power point tracking is similar to impedance matching by a transformer for alternating current. In direct current, a DC-DC converter is used to convert the solar cell's output voltage relative to Pmax by changing the duty cycle [20].

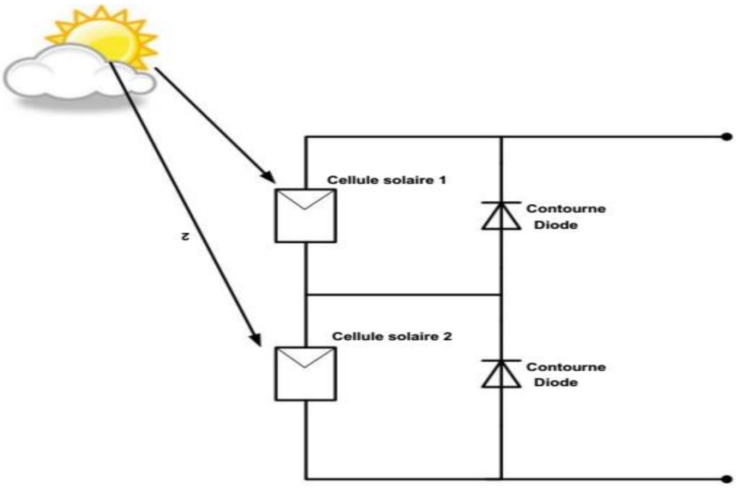


Figure II-3: Operation of PV Solar in Partial Shading Conditions [20].

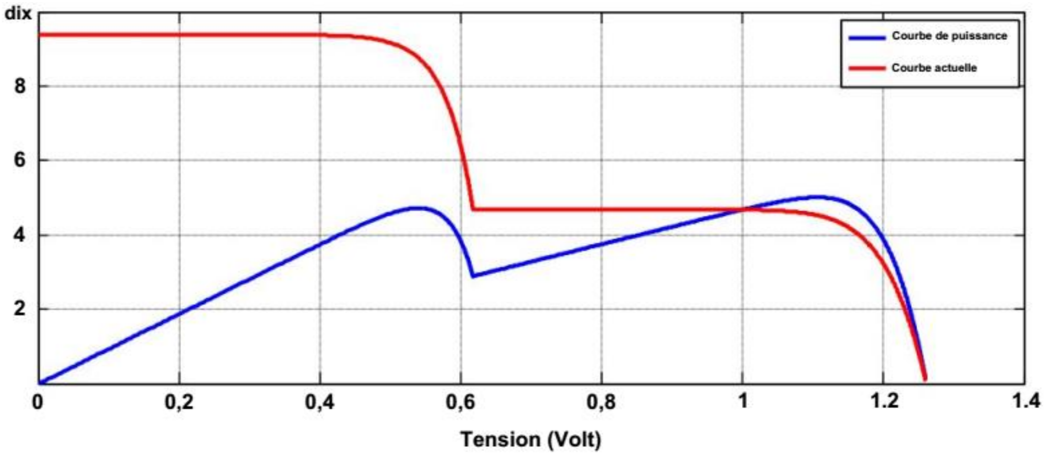


Figure II-4: I-V and P-V Curve in Partial Shading Conditions [20].

## II.3. MPPT Approach

We will now review the MPPT solutions currently available in the market [7].

### II.3.1. Perturb and Observe Approach

The principle of Perturb and Observe (P&O) type MPPT control is to perturb the PV voltage VPV with a low amplitude around its initial value and analyze the behavior of the resulting power variation PPV. As illustrated in Figure I.21, one can deduce that if a positive increment in voltage VPV results in an increase in power PPV, it means the operating point is to the left of the MPP. Conversely, if the power decreases, it implies that the system has exceeded the MPP. Similar reasoning can be applied when the voltage decreases. Based on these analyses of the consequences of voltage variation on the PPV(VPV) characteristic, it is then easy to position the operating point relative to the MPP and converge it towards maximum power through an appropriate control command.

In summary, if, following a voltage disturbance, the PV power increases, the perturbation direction is maintained. Otherwise, it is reversed to regain convergence towards the new MPP [21].

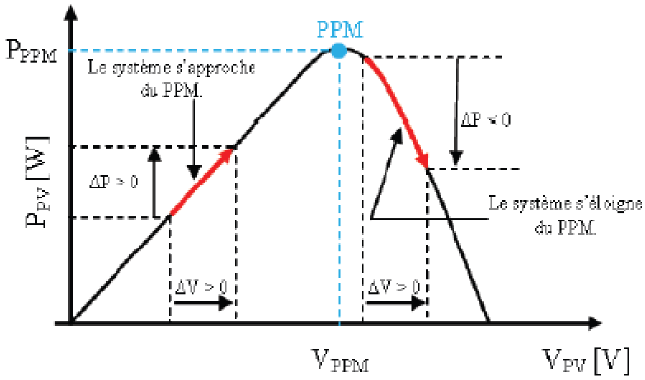


Figure II-5: PPV(VPV) Characteristic and Operation of the Perturb and Observe Method

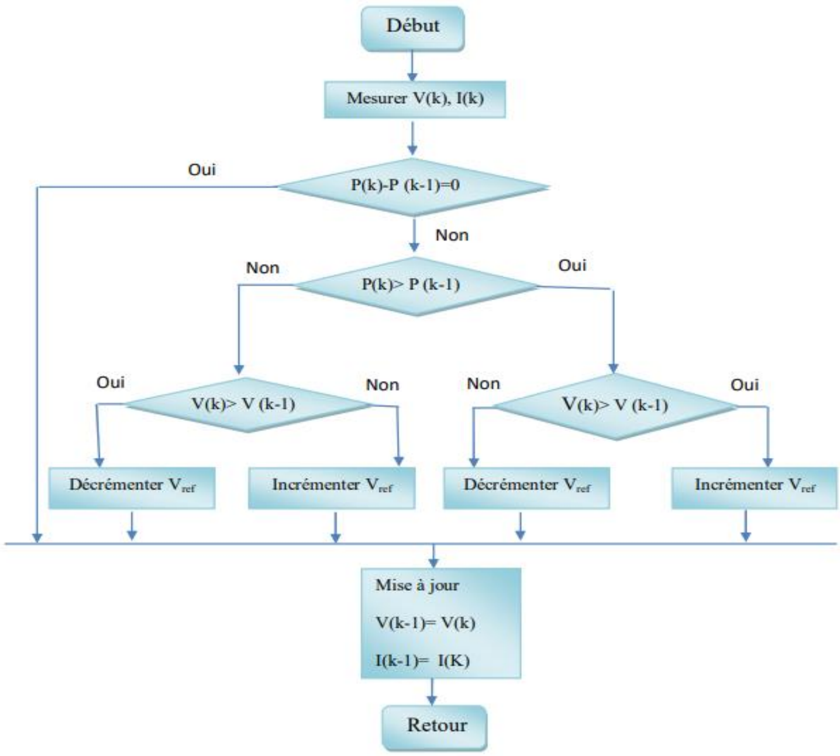


Figure II-6: Flowchart of the Perturb and Observe Method [22].

Figure I.22 represents the classic algorithm associated with P&O type MPPT control, where power evolution is analyzed after each voltage perturbation. For this type of control, two sensors (current and voltage of the PV generator) are required to determine the PV power at each instant.

## II.4. Simulation of the "P&O" Digital MPPT Control:

In practice, ideal conventional conditions are rarely met, and the variation of these conditions is random and unpredictable. Changes in sunlight and temperature directly affect the current-voltage and power-voltage characteristics. Hence, the integration of an MPPT control is essential [23].

Simulation of the MPPT Method:

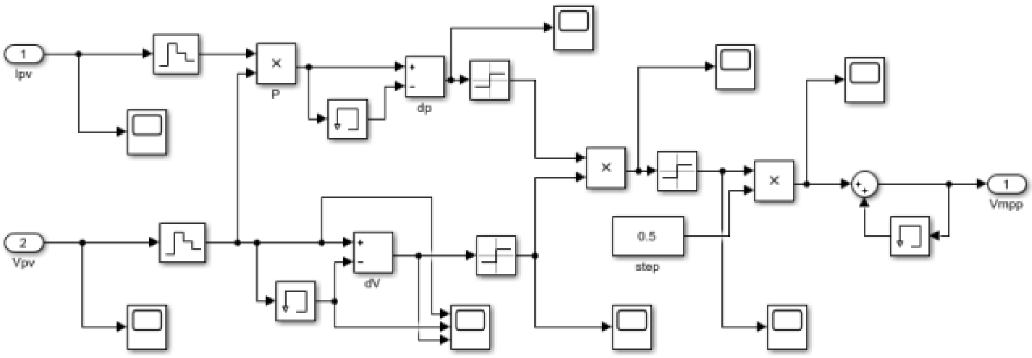


Figure II-7 illustrates the block diagram of the (P&O) algorithm.

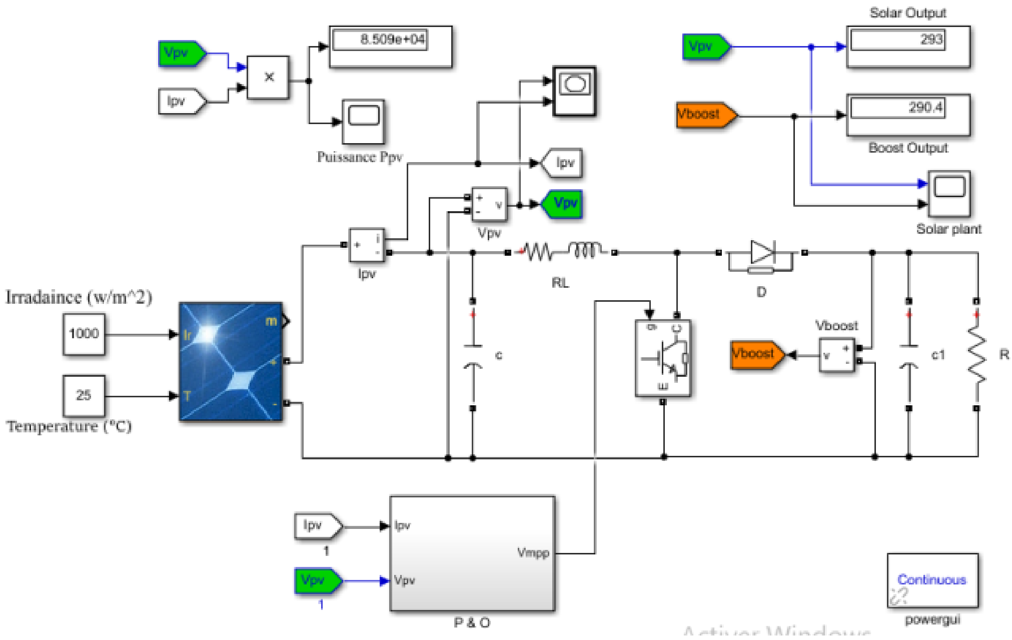


Figure II-8 displays the schematic of the Boost converter controlled by MPPT.

### II.4.1. Simulation Results

The following figures represent simulation results of the PV panel and DC-DC converter association for G=1000 W/m2 and T=25°C:

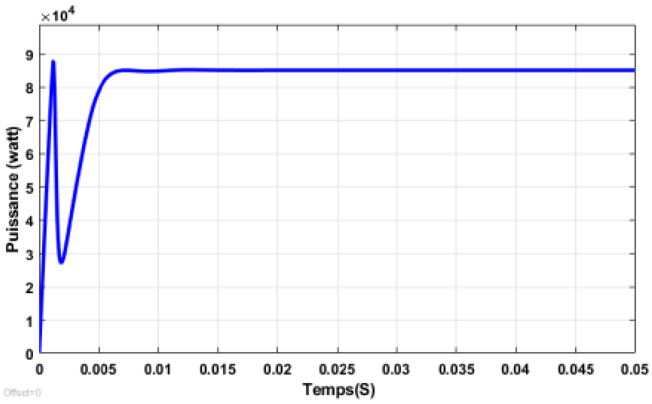


Figure II-9: Power profile over time for (T=25°C, G=1000W/m²).

From Figure I-25, it can be observed that the power takes approximately 0.01 seconds to reach a steady-state characterized by minor oscillations, stabilizing at the maximum value of 85KW.

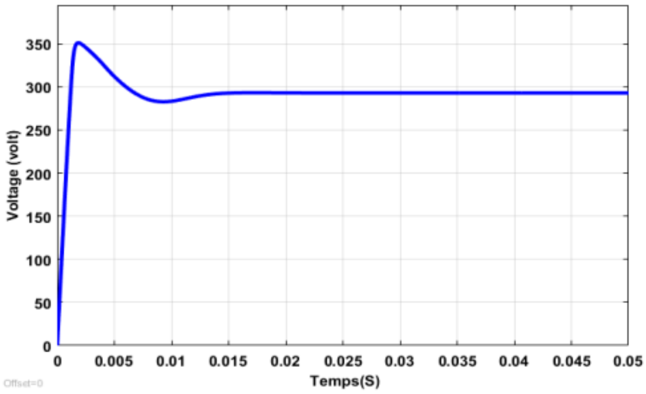


Figure II-10: Voltage profile over time for (T=25°C, G=1000W/m²).

According to Figure I-26, the voltage goes through a transient phase lasting 0.01 seconds, characterized by an increase up to 350 V, followed by stabilization at the maximum value of 293 V in the steady state.

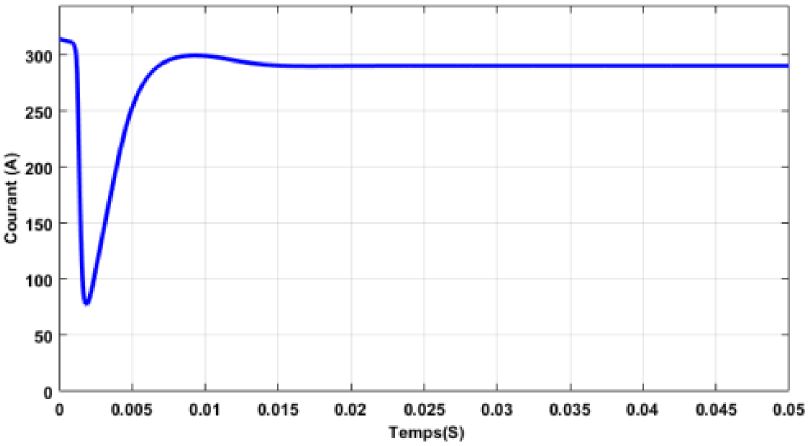


Figure II-10: Current profile over time for (T=25°C, G=1000W/m²).

From Figure I-27, it can be observed that during the period from 0 to 0.01 seconds, the current increases abruptly, then decreases with significant oscillations before stabilizing at the maximum value of 290 A.

**II.4.2. Photovoltaic Installation Performance Index (Quality Factor):**

The performance index is one of the most critical values for assessing the efficiency of a photovoltaic installation. In essence, the performance index represents the ratio between the actual energy yield and the theoretically achievable energy yield. It is largely independent of the orientation of the photovoltaic installation and the radiation on the photovoltaic installation. Therefore, the performance index allows for comparisons of grid-connected photovoltaic installations in various locations worldwide.

The closer the value of a photovoltaic installation gets to 100%, the more efficient the installation operates. However, it is not practically possible to reach a value of 100% because the operation of the photovoltaic installation always incurs losses, which are inevitable (e.g., thermal losses due to the heating of photovoltaic panels). Nevertheless, high-performing photovoltaic installations can achieve a performance index of up to 80% [7].

**II.4.2.1.** Environmental Factors:

- Temperature of the photovoltaic panels
- Solar radiation and energy dissipation
- Shading or soiling of the photovoltaic panels
- Shading or soiling of the measuring device (e.g., Sunny SensorBox) [7].

**II.4.2.2.** Other Factors:

- Recording period
- Losses in the lines
- Different solar technologies of the measuring device (e.g., Sunny SensorBox) and photovoltaic panels
- Orientation of the measuring device (e.g., Sunny SensorBox)
- Efficiency coefficient of the photovoltaic panels
- Efficiency coefficient of the inverter [7].

## II.5. Conclusion

In summary, this chapter has provided an in-depth exploration of the strategies employed to maximize power point tracking (MPPT) in photovoltaic systems. We have gained insights into the fundamental principles and various techniques utilized in MPPT, recognizing its pivotal role in optimizing energy conversion within solar systems.

The chapter commenced with an introduction that underscored the significance of MPPT and its critical function as a core component in solar energy systems. We have come to understand that MPPT operates as a sophisticated DC/DC converter, adeptly harnessing the energy generated by solar cells.

Moving forward, we delved into the pursuit of the Maximum Power Point Tracker, comprehending its operational principles and efficiency. Notably, we observed that MPPT exhibits superior performance in specific scenarios, such as cold weather conditions and high battery discharge depths.

Moreover, we examined the profound impact of environmental variables, including insolation, temperature, and partial shading, on the performance of the MPPT regulator. These factors were found to exert significant influence on the characteristics of solar cells, ultimately shaping their operational effectiveness.

The Perturb and Observe (P&O) approach, a prominent MPPT control strategy, was thoroughly elucidated. We gained a comprehensive understanding of how this method effectively perturbs the PV voltage to ascertain the maximum power point, exemplifying its practical applicability.

Finally, we presented simulation results of the digital MPPT control method, offering valuable insights into the performance of photovoltaic systems under diverse conditions.

Looking ahead to the next chapter, our focus will shift towards neural networks, exploring their role and applications in the realm of photovoltaic systems.

# Chapter III:

## Fundamentals of Artificial Neural Networks and Their Applications

## III.1. Introduction

An artificial neural network, or artificial neuronal network, is a system whose design was originally schematically inspired by the functioning of biological neurons and subsequently converged with statistical methods. Neural networks are typically optimized using probabilistic learning methods, particularly Bayesian. They are positioned, on one hand, within the realm of statistical applications, enhancing it with a set of paradigms for rapid classifications (notably Kohonen networks), and on the other hand, within the family of artificial intelligence methods. They provide an independent perceptual mechanism, distinct from the implementer's own ideas, and input information for formal logical reasoning (see Deep Learning). In the field of modeling biological circuits, they enable the testing of certain functional hypotheses derived from neurophysiology or examining the consequences of these hypotheses to compare them with real-world data.

## III.2. Historical Overview

Neural networks are constructed upon a biological paradigm, specifically that of the formal neuron, akin to how genetic algorithms draw inspiration from natural selection. This biological metaphor gained prominence alongside the concepts of cybernetics and biocybernetics. As per Yann Le Cun's articulation, it does not purport to describe the brain any more than an airplane wing replicates that of a bird [5]. Notably, glial cells' role is not emulated.

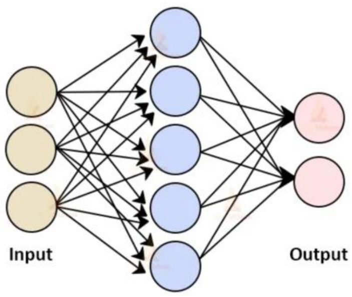


Figure III.1. Simplified view of an artificial neural network

The history of neural networks extends further back than commonly realized. While the notion of a "thinking machine" can be traced back to ancient Greece, our focus centers on pivotal milestones that steered the development of neural network thinking, with its popularity ebbing and flowing over the years:

1. 1943: Warren S. McCulloch and Walter Pitts published "A logical calculus of the ideas immanent in nervous activity." This research aimed to fathom how the human brain generates intricate patterns via interconnected brain cells, i.e., neurons. A pivotal concept to emerge from this work was the analogy between binary threshold neurons and Boolean logic, characterized by 0/1 or true/false instructions.
2. 1958: Frank Rosenblatt is accredited with the development of the perceptron, documented in his research titled "The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain." Rosenblatt took a stride beyond McCulloch and Pitt by introducing the notion of weights into the equation. Leveraging an IBM 704, Rosenblatt successfully taught a computer to distinguish cards marked on the left from those marked on the right.
3. 1974: While numerous researchers contributed to the concept of backpropagation, Paul Werbos became the first person in the United States to observe its applicability in neural networks in his doctoral thesis.
4. 1989: Yann LeCun published an article illustrating how constraints in backpropagation and their integration into neural network architecture could be harnessed for algorithm training. This research harnessed a neural network to recognize handwritten digits derived from postal codes furnished by the United States Postal Service.

## III.3. Functioning of Artificial Neural Networks

Typically, an artificial neural network relies on a large number of processors operating in parallel and organized into layers. The first layer receives raw information inputs, somewhat akin to the optic nerves in the human visual signal processing.

Subsequently, each layer receives information outputs from the preceding layer. This process mirrors the human experience, where neurons receive signals from neurons close to the optic nerve. The final layer, on the other hand, produces the system's outcomes.

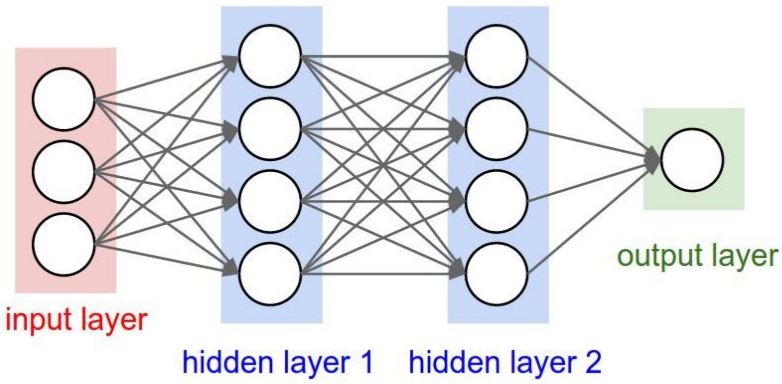


Figure III.2. Functioning of Artificial Neural Networks

Through an algorithm, artificial neural networks enable computers to learn from new data. Computers equipped with neural networks learn to perform a task by analyzing examples for training. These examples have been previously labeled, allowing the network to understand what they represent.

For instance, an artificial neural network can be employed to teach a computer object recognition. A large set of objects from the same category is presented to the neural network, and the computer learns to identify this object in new images by analyzing recurring patterns within the example images. Hence, by scrutinizing thousands of cat photos, the neural network will learn to recognize a cat in any given picture.

Unlike other types of algorithms, neural networks cannot be directly programmed to perform a task. Similar to a child's developing brain, their sole directive is to learn.

However, three distinct learning methods are distinguished:

1. **Supervised Learning**: In this method, the algorithm trains on a set of labeled data and adjusts itself until it can process the dataset to achieve the desired outcome.
2. **Unsupervised Learning**: Data in this case is unlabeled. The neural network analyzes the dataset, and a cost function informs it of how far it deviates from the desired result. The network adapts to enhance the algorithm's accuracy.
3. **Reinforcement Learning**: Here, the neural network is reinforced for positive results and penalized for negative ones. This enables it to learn and improve over time, in the same way that a human gradually learns from their mistakes.

## III.4. Applications

Artificial neural networks, with their classification and generalization capabilities, find extensive use in various statistical problems. They are effectively employed in:

1. Animal Species Classification from DNA Analysis: Neural networks are used for classifying animal species based on DNA analysis.
2. **Image Classification:** Neural networks excel in image classification tasks, such as pattern recognition. Examples include optical character recognition (OCR) for banks to verify check amounts and postal services to sort mail by postal codes. They are also used in the automation of autonomous mobile robots.
3. **Function Approximation:** Neural networks can approximate unknown functions.

4. **Accelerated Modeling of Complex Functions:** They expedite the modeling of known but computationally complex functions. For instance, certain inversion functions are employed to decode remote sensing signals from satellites into sea surface data.
5. **Time Series Estimations:** Neural networks are applied in time series analysis, such as sensor data analysis.
6. **Speech Recognition and Music Recognition:** They are used in speech and music recognition applications.
7. **Modeling Chaotic Systems:** Neural networks find application in meteorology for atmospheric condition classification and statistical weather forecasting. They are also used in the inspection of hydraulic structures to understand physical phenomena related to displacements, subpressures, and leakage flows.
8. **MPPT (Maximum Power Point Tracking) in Photovoltaic Systems**: Artificial neural networks are utilized in the optimization of MPPT, a critical component in photovoltaic systems. They enhance the efficiency of solar energy capture by continuously adjusting the operating point of photovoltaic panels to maximize power output, considering varying environmental conditions such as insolation, temperature, and shading. This enables photovoltaic systems to harness solar energy more effectively and increase overall energy production.

These examples demonstrate the versatility and practical utility of artificial neural networks across diverse fields and problem domains, including their valuable role in optimizing photovoltaic systems through MPPT.

## III.5. Conclusion

In summary, an artificial neural network, or Neural Network, is a computer system inspired by the functioning of the human brain to facilitate learning. This technology belongs to the realm of Artificial Intelligence, particularly within the Deep Learning family. It offers a powerful approach to problem-solving and data analysis, finding applications in various domains ranging from image recognition to weather forecasting and optimizing photovoltaic systems through MPPT. As artificial neural networks continue to evolve and advance, they hold the potential to drive further innovations and enhancements in the field of artificial intelligence and beyond.

# Chapter IV:

## Bridging Theory and Practice – Implementing MPPT with ANNs in MATLAB

## IV.1. Introduction

In this introductory section, our primary objective is to orient the reader towards the core theme of Chapter IV, which revolves around the practical implementation of Maximum Power Point Tracking (MPPT) techniques employing Artificial Neural Networks (ANNs) within the MATLAB environment. This chapter is the bridge between theory and real-world application, where we translate theoretical concepts discussed in previous chapters into hands-on, tangible solutions.

As we progress, we will delve into the methodological intricacies of our approach, which involves training ANNs using data collected from simulations of the Perturb and Observe (P&O) MPPT method under diverse climatic scenarios. The critical aim is to demonstrate how ANNs can enhance MPPT efficiency in photovoltaic systems and, in the process, contribute to the sustainable utilization of solar energy.

By the end of this chapter, readers will gain a profound understanding of how ANNs can be effectively employed to optimize photovoltaic systems' performance, and they will be equipped with insights into the practical aspects of implementing these technologies within a MATLAB-based simulation framework.

Through a detailed exploration of data collection, preprocessing, ANN architecture, training processes, and performance evaluation, this chapter lays the groundwork for the subsequent discussions, providing a comprehensive view of the practical integration of ANNs in enhancing the efficiency and sustainability of solar energy generation.

## IV.2. Methodology:

In this section, we present a comprehensive breakdown of the methodology employed in this chapter, a critical component in implementing Maximum Power Point Tracking (MPPT) techniques using Artificial Neural Networks (ANNs) within the MATLAB environment. The methodology comprises the following key steps:

➢ **Data Collection:**

The initial phase of our methodology involves the collection of data from simulations of the Perturb and Observe (P&O) MPPT method conducted under a diverse range of climatic scenarios. Data collection serves as the cornerstone for training and evaluating our ANN-based MPPT model. This subsection provides detailed insights into the data collection process, encompassing the selection of climatic variables, simulation parameters, and the duration of data acquisition.

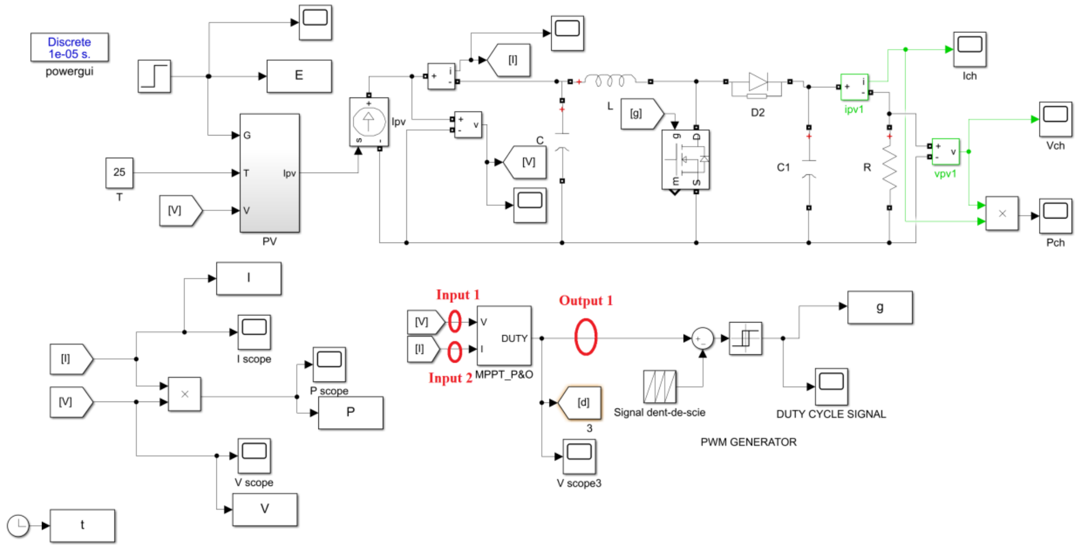


**Figure IV.1**: Data Collection Process

This visualization elucidates the meticulous data collection procedure employed during simulations of the Perturb and Observe (P&O) Maximum Power Point Tracking (MPPT) method across a spectrum of diverse climatic scenarios. The central focus is on the acquisition of pertinent data, specifically input variables, and their influence on the sole output variable, the duty cycle denoted as 'd,' over a simulation period of 0.5 seconds. To maintain consistency, a discrete time interval (Ts) of 1e-5 is applied, ensuring precision and reliability throughout the process. This figure serves as an essential reference, encapsulating the fundamental stages of data aggregation vital for the subsequent training and assessment of the ANN-driven MPPT model.

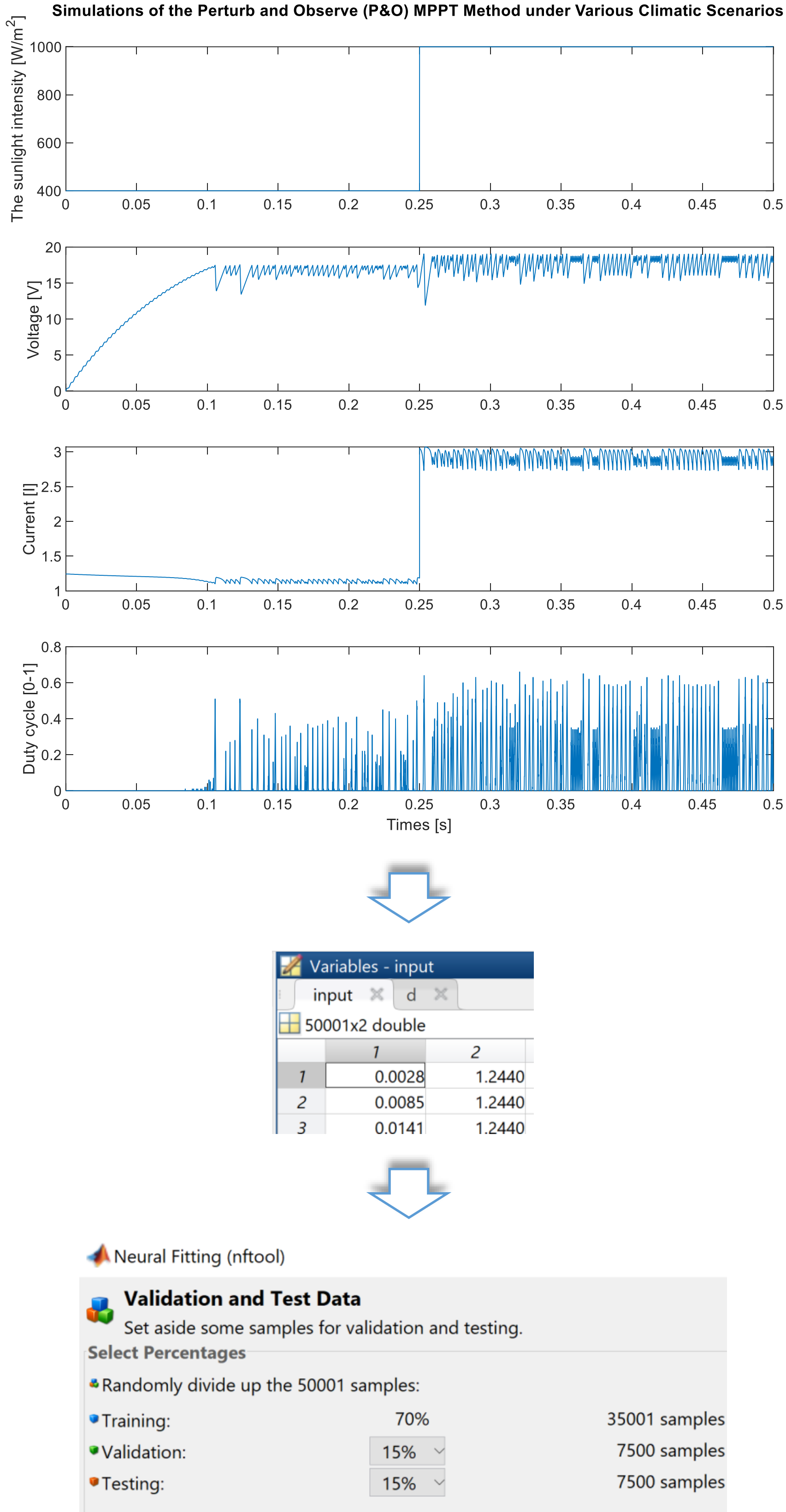


**Figure VI.2:** Data Preprocessing Workflow

This figure provides a visual representation of the meticulous data preprocessing workflow, an integral component of our methodology. The primary objective is to ensure that the collected data, comprising input variables [V, I], and the output variable [d], is thoroughly prepared for subsequent training and evaluation of our Artificial Neural Network (ANN) model.

- **Data Cleaning:**

In the initial phase of data preprocessing, we address any inconsistencies, outliers, or missing values within the dataset of 50,001 data points. This critical step is paramount to maintain dataset integrity and eliminate potential sources of error.

- **Normalization:**

Data normalization is of utmost importance to bring all features to a consistent scale. By applying appropriate normalization techniques to the 50,001 data points, we guarantee that no feature dominates the training process, thus preventing bias during ANN training.

- **Feature Selection:**

Feature selection is a key determinant of model performance. Our approach to feature selection involves identifying the climatic parameters and variables with the most significant influence on Maximum Power Point Tracking (MPPT) optimization. These selected features are crucial for the accuracy and efficiency of our ANN model.

Figure VI.2 serves as a visual guide, offering a comprehensive overview of the essential steps taken to meticulously prepare the collected data for the subsequent phases of ANN model training and analysis.

Following the execution of the Perturb and Observe (P&O) simulation and the collection of data, it is allocated within the Neural Fitting (nftool) tool as follows:

- Training: 70% (35,001 samples)
- Validation: 15% (7,500 samples)
- Testing: 15% (7,500 samples)

### IV.2.1. Implementation of MPPT with ANNs using MATLAB:

This section delves into the practical steps associated with implementing Maximum Power Point Tracking (MPPT) using Artificial Neural Networks (ANNs) in the MATLAB environment:

- **ANN Architecture:** In this part, the neural network's structure is elucidated, encompassing details such as the number of layers, neurons, and the activation functions employed.

**Hidden Layer**

Define a fitting neural network. (fitnet)

Number of Hidden Neurons: 10

**Figure VI.3:** Network Configuration for Hidden Layer with 10 Neurons

This figure provides an overview of the network configuration settings, focusing on the critical component known as the hidden layer within the fitting neural network. The figure emphasizes the selected configuration, which includes a hidden layer comprising 10 neurons.

- **Training Process:**

In this section, we delve deeply into the intricate details of training the Artificial Neural Network (ANN) using the meticulously collected and preprocessed dataset. We explore the various facets of the training process, including the selection of appropriate training algorithms and their associated parameters.

The training of our neural network involves the process of modeling the intricate relationships between the input and target variables. This phase is fundamental to the successful functioning of the ANN.

The choice of a training algorithm significantly influences the learning process of the neural network. For our implementation, we opt for the Levenberg-Marquardt algorithm. This particular algorithm is preferred due to its characteristic of requiring more memory while saving time. It automatically halts the training process when there is no further improvement in generalization, typically indicated by an increase in the mean square error of the validation samples.

Within the training process, there may be instances where the network undergoes retraining. This additional training step aims to further enhance the network's performance and improve its adaptability to the underlying data patterns.

- **Performance Evaluation:** This subsection is dedicated to the assessment of the implemented ANN-based MPPT system:

**Results**

| | Samples | MSE | R |
|---|---|---|---|
| Training: | 35001 | 1.28073e-3 | 9.66151e-1 |
| Validation: | 7500 | 1.31020e-3 | 9.66433e-1 |
| Testing: | 7500 | 1.23333e-3 | 9.67396e-1 |

**Figure VI.4:** Training Results

This figure presents the training results of the Artificial Neural Network (ANN) model for Maximum Power Point Tracking (MPPT) implementation. The results are displayed in tabular format, showcasing critical metrics such as the number of samples, Mean Squared Error (MSE), and the coefficient of determination (R-squared) for both the training and validation/testing phases.

In the table, the training phase consists of 35,001 samples, achieving an MSE of approximately 1.28073e-3 and an R-squared value of about 0.96615. Similarly, the validation/testing phase comprises 7,500 samples, with an MSE of approximately 1.31020e-3 and an R-squared value of around 0.96643. These metrics serve as indicators of the ANN model's performance and its ability to accurately predict and optimize the MPPT process.

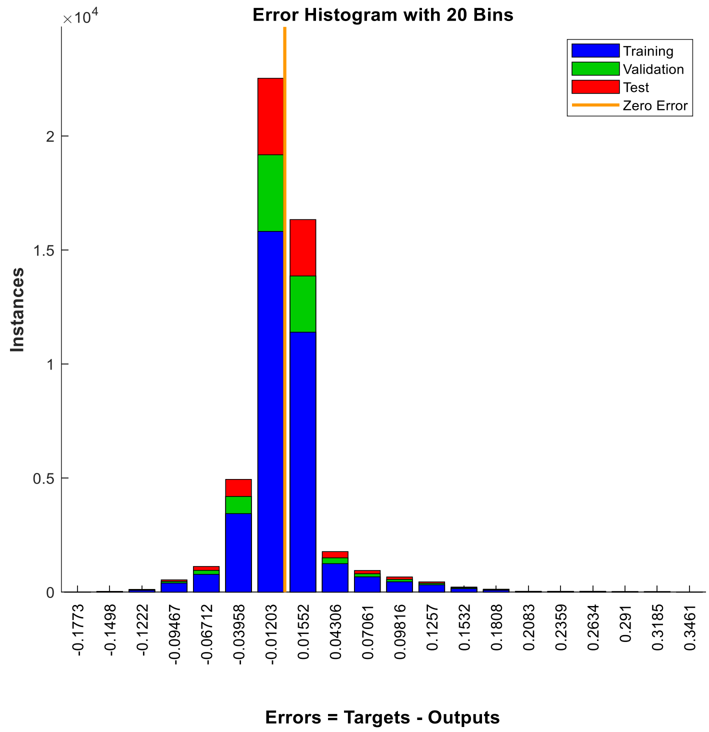


**Figure VI.5:** Error Histogram with 20 Bins

This figure displays an error histogram with 20 bins, providing a visual representation of the distribution of errors in the ANN model for Maximum Power Point Tracking (MPPT) implementation. The histogram includes data from the training, validation, and testing phases.

The x-axis represents the error values, while the y-axis indicates the frequency or count of errors within each bin. The histogram allows us to assess the accuracy and consistency of the ANN model's predictions by observing the error distribution. In an ideal scenario, errors should be concentrated around zero, indicating minimal discrepancies between the model's outputs and the target values. The histogram's shape and spread provide valuable insights into the model's performance and its ability to predict MPPT accurately.

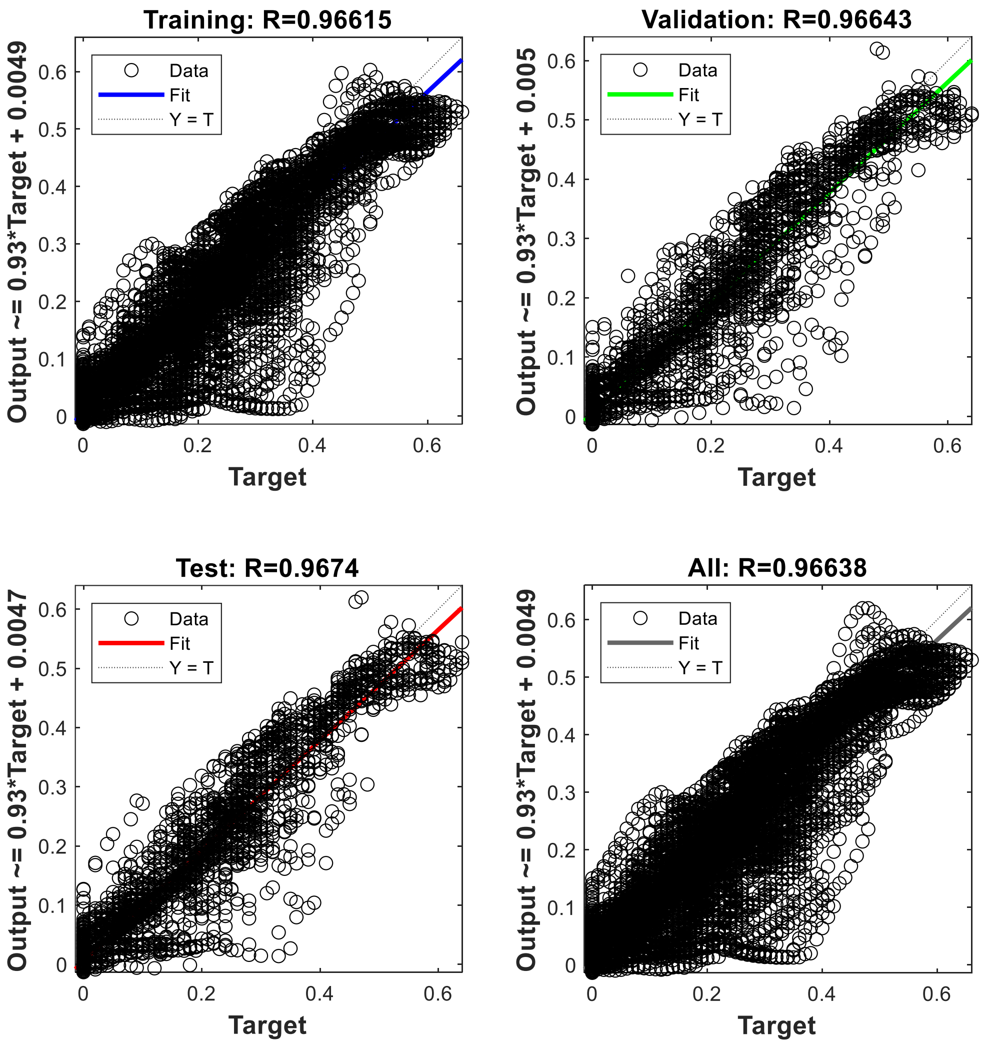


**Figure VI.6:** Model Performance Comparison

This figure provides a visual comparison of the model's performance in predicting the Maximum Power Point (MPP) for photovoltaic systems. The plot illustrates how well the ANN model aligns with the target values (Y = T) for training, testing, validation, and all datasets.

Each curve represents a different regression equation (Output ~= 0.93* Target + [a constant term]) fitted to the data. The coefficient of determination (R) is indicated for each dataset, reflecting the goodness of fit. A higher R-value indicates a closer fit between the model's predictions and the actual target values.

The plot allows for a quick assessment of how effectively the model captures the MPP, with higher R-values indicating better performance. It demonstrates that the model closely aligns with the target values across all datasets, highlighting its accuracy and reliability in predicting the MPP for various environmental conditions.

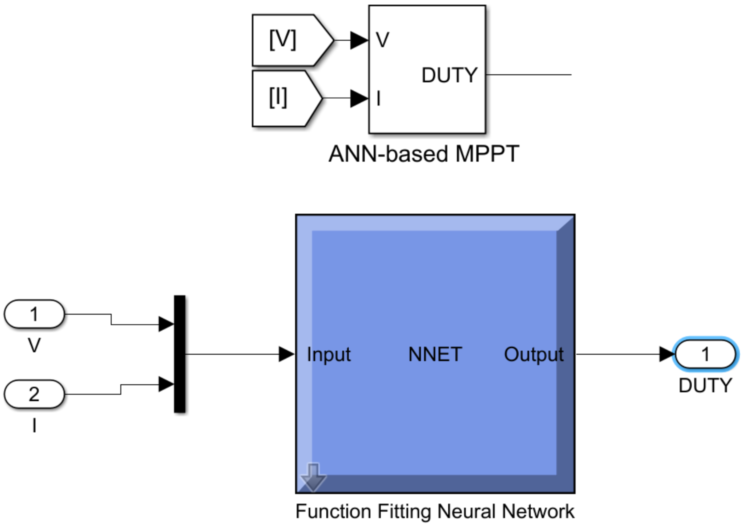


**Figure VI.7:** Neural Network Architecture for MPPT

This figure illustrates the neural network architecture designed for Maximum Power Point Tracking (MPPT) in photovoltaic systems. The diagram showcases the structure and function of the Artificial Neural Network (ANN) responsible for predicting the duty cycle (DUTY) based on input voltage (V).

- Input (V): This represents the input layer of the neural network, which takes the voltage (V) as an input feature.
- Function Fitting Neural Network: This layer represents the core of the ANN, where the computational processing occurs. It includes hidden layers and neurons responsible for learning and making predictions.
- Output (DUTY): This is the output layer that provides the predicted duty cycle (DUTY) as the result of the network's computations.

The neural network is trained to approximate the relationship between input voltage (V) and the corresponding duty cycle (DUTY) using the collected dataset. This architecture enables the ANN to effectively optimize the photovoltaic system's performance by determining the maximum power point under varying environmental conditions.

### IV.2.2. Comparison with Traditional Methods:

Compare the performance of the ANN-based approach with traditional MPPT methods, emphasizing any improvements achieved.

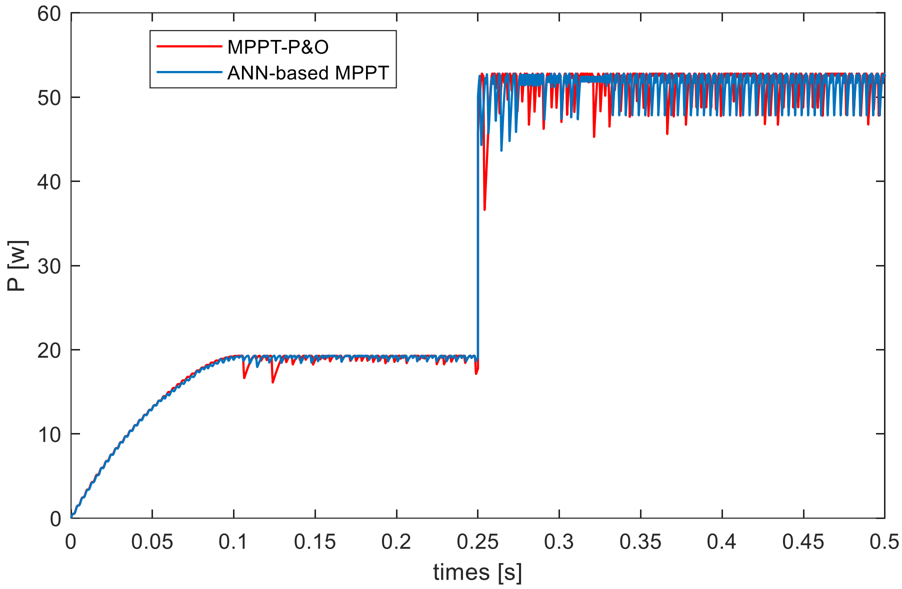


**Figure VI.8:** Performance Comparison between MPPT-P&O and ANN-based MPPT

This figure presents a comparative analysis of the performance between two Maximum Power Point Tracking (MPPT) methods: the traditional Perturb and Observe (P&O) MPPT method and the Artificial Neural Network (ANN)-based MPPT approach.

The graph allows for a visual assessment of the effectiveness of the ANN-based MPPT approach compared to the conventional P&O method. It indicates whether the ANN-based approach leads to improved power generation, especially during conditions where the traditional method may not perform optimally.

## IV.3. Results and Discussion:

In this crucial section, we present the outcomes of the simulations and discuss their implications:

**Scenarios 1:** E=500 W/m² at 0 s to 800 W/m² at 0.25 s

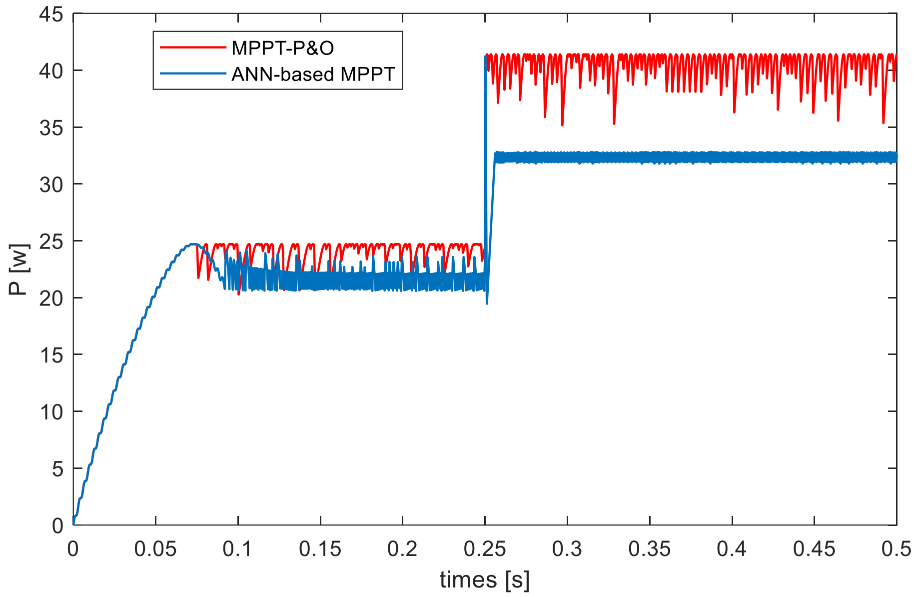


Figure VI.9: Performance Comparison between MPPT-P&O and ANN-based MPPT (E=500 at 0 s to 800 at 0.25 s)

In this scenario, we examine the performance of two Maximum Power Point Tracking (MPPT) methods under varying irradiance conditions, specifically from 500 W/m² at 0 seconds to 800 W/m² at 0.25 seconds.

Upon close examination, it is evident that the ANN-based MPPT method did not converge to the tripoint, which allows for maximum power extraction. Instead, it fell short of achieving the optimal point. Conversely, the MPPT-P&O method outperformed the ANN-based approach noticeably.

This scenario underscores the importance of evaluating MPPT methods under diverse environmental conditions, as the choice of method can significantly impact energy harvesting efficiency.

**Scenarios 2:** Diverse Environmental Conditions

The data was gathered once more, considering the diverse weather conditions, to conduct simulations of the Perturb and Observe (P&O) MPPT method. Subsequently, the neural network was trained on this newly collected dataset.

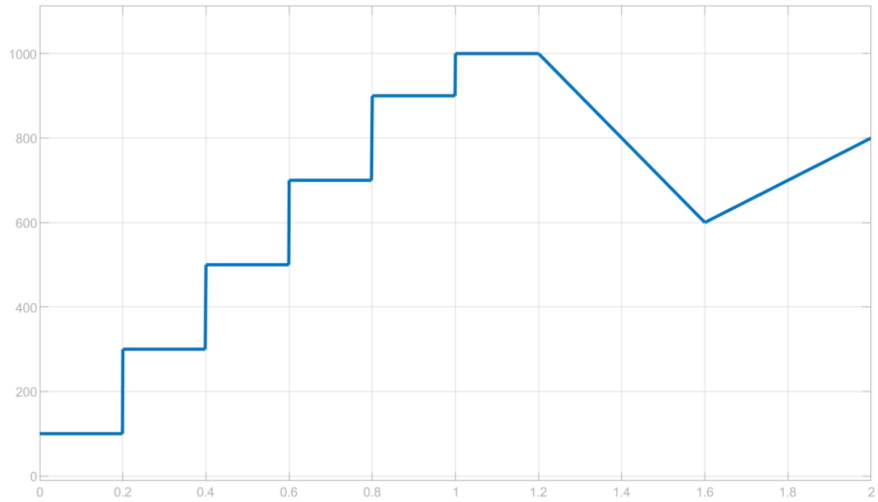


**Figure VI.10:** Variation of Sunlight Intensity Over Time

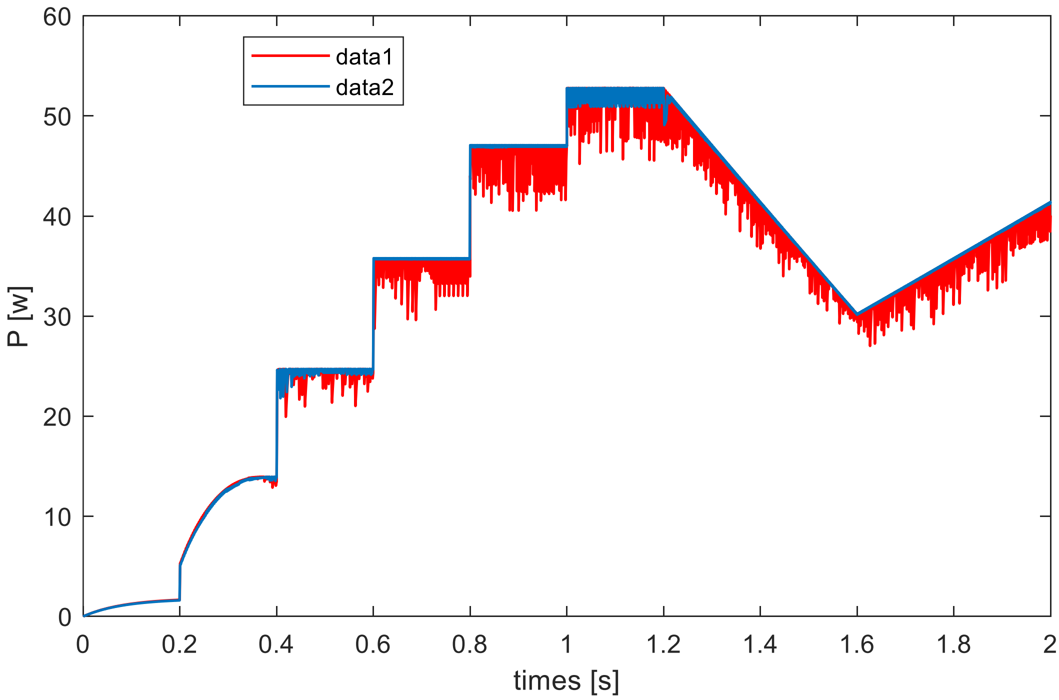


**Figure VI.11:** Performance Comparison between MPPT-P&O and ANN-based MPPT

Figure VI.10 illustrates the dynamic changes in sunlight intensity over time, serving as a visual representation of the varying environmental conditions experienced during the simulations.

Figure VI.11 offers a performance comparison between the traditional Perturb and Observe (P&O) MPPT method and the ANN-based MPPT approach. It visually showcases the differences in power output under different scenarios, providing valuable insights into the effectiveness of each method.

## IV.4. Conclusion:

In conclusion, this chapter has delved into the practical implementation of Maximum Power Point Tracking (MPPT) techniques using Artificial Neural Networks (ANNs) within the MATLAB environment. The methodology involved data collection and preprocessing, network configuration, training, and performance evaluation. We observed the intricate steps taken to prepare and train the ANN for MPPT optimization.

Additionally, this chapter explored the comparison between the ANN-based MPPT approach and traditional methods under diverse environmental scenarios. The results shed light on the advantages and limitations of each approach, paving the way for further analysis and refinement.

As we move forward in this research journey, Chapter V will delve into the real-world applications and testing of our ANN-based MPPT model. We will assess its performance under various conditions and evaluate its potential contributions to the field of renewable energy. This exploration will offer valuable insights into the practicality and effectiveness of our proposed approach.

# General Conclusion

## General Conclusion

In summary, this thesis has journeyed through the realm of enhancing photovoltaic systems through the integration of Artificial Neural Networks (ANNs) for Maximum Power Point Tracking (MPPT) optimization. We commenced with a thorough exploration of photovoltaic systems, highlighting their significance as a source of clean and renewable energy. We then navigated through the intricacies of MPPT, recognizing its crucial role in maximizing energy capture from varying environmental conditions.

The core of our research involved the integration of ANNs into photovoltaic systems, capitalizing on their adaptability and learning capabilities inspired by the human brain. We meticulously examined the synergy between ANNs and photovoltaics, considering their role in dynamic adaptation to changing environmental factors.

Practical implementation was a pivotal phase, showcased in Chapter IV, where we detailed data collection, preprocessing, neural network architecture, training, and performance evaluation. Our research illuminated the differences between ANN-based MPPT and traditional methods under diverse environmental scenarios.

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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